Transparency, Control, and Pay in the Gig Economy: A Game-theoretic Perspective

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Abstract

The transparency and control of earnings are major concerns for gig economy workers across platforms such as ride-hailing and food delivery. While workers advocate for greater transparency, platforms selectively disclose information, shaping workers' decision-making and earnings. Recently, the Federal Trade Commission (FTC) has highlighted lack of transparency as a key issue, and platforms have responded by introducing upfront pay quotes that provide per-trip compensation details for workers. Using a game-theoretic model, we analyze the strategic interactions between the platform and workers, incorporating tools from information design to examine how different transparency policies—specifically, a fixed commission rate versus upfront pay quotes—shape equilibrium outcomes. We find that greater transparency can paradoxically increase platform control, as it allows platforms to fine-tune pay structures in ways that ultimately reduce worker autonomy. Moreover, while full information benefits the platform when it has flexibility in commission setting, it can backfire under commitment constraints, leading to lower profits than a no-information policy. Our findings highlight that transparency is not inherently beneficial for workers. Instead, its effects depend on how it interacts with pay policies. In particular, simple mechanisms, such as a fixed commission rate, can provide workers with more stability and bargaining power than per-trip transparency. These insights offer important guidance for policymakers and platform designers navigating the trade-offs of transparency in the gig economy.

Key words: Platforms, transparency, queueing, gig economy, information design

1 Introduction

Transparency and control have emerged as critical pain points for gig economy workers across platforms such as ride-hailing, food delivery, and casual labor. Numerous social events and news headlines underscore this issue. For example, on May 1, 2024, Lyft and Uber drivers gathered at the

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Georgia State Capitol to demand better pay and greater transparency (Francisco 2024). Such events are not isolated incidents. Gig economy platforms, which mediate transactions between service providers and customers, operate as intermediaries with access to extensive market information. However, the extent to which they share this information with workers is left to their discretion, often resulting in significant dissatisfaction among workers.

In response to these concerns, the U.S. Federal Trade Commission (FTC) issued a statement on September 12, 2022, titled "FTC to Crack Down on Companies Taking Advantage of Gig Workers."(Federal Trade Commission 2022) The statement identified "lack of transparency" as one of the three major challenges in the gig economy, noting that, "*workers have little leverage to demand transparency from gig companies, even in the face of unclear information about when work will be available, where they will have to perform it, or how they will be evaluated.*"

Yet, improving transparency and control for gig workers is a complex issue with many interrelated factors. First, differing interpretations of transparency can result in vastly different policies, the implications of which are not well understood. Even when transparency is provided, it is unclear whether it necessarily aligns with greater control for workers. Additionally, from a practical perspective, transparency must be embedded in policies or contracts that are not only implementable but also trusted by workers. To illustrate these challenges, we present two examples of prevalent worker pay policies commonly used in the ride-hailing industry.

Example 1: A flat commission rate. A common worker pay structure in the gig economy is a fixed (flat) commission rate model. For example, Uber used to take about 25% of the ride value as its revenue and pass 75% to the drivers (Payroll 2020). Lyft also commits to drivers a share of rider payment of about 70% (Lyft 2024a). Under this policy, the platform can be viewed as selecting a single commission rate, and commits to this commission rate for all requests. Workers know about this commission rate but do not know the specific pay of each job they receive.

Example 2: An upfront quote. This is the recent Lyft upfront pay model (Lyft 2024b) and Uber's upfront fares model (Uber 2024). Under these models, the platform reveals a quote for each job dispatched to the workers, allowing the workers to see precisely how much they will be compensated if they choose to accept the job.

Fig. 1 illustrates the change of the Uber driver's app interface before and after the introduction of Upfront Fares. On the left, prior to 2022, drivers did not see the exact pay information for a ride but instead relied on a general understanding of the commission rate as an anchor, similar to the flat rate model described above. On the right, in the post-Upfront Fares model, the app provides an accurate upfront estimate of the pay for each trip, consistent with the upfront quote model described above.

The two examples illustrate the complexity of analyzing information policies in gig economy plat-

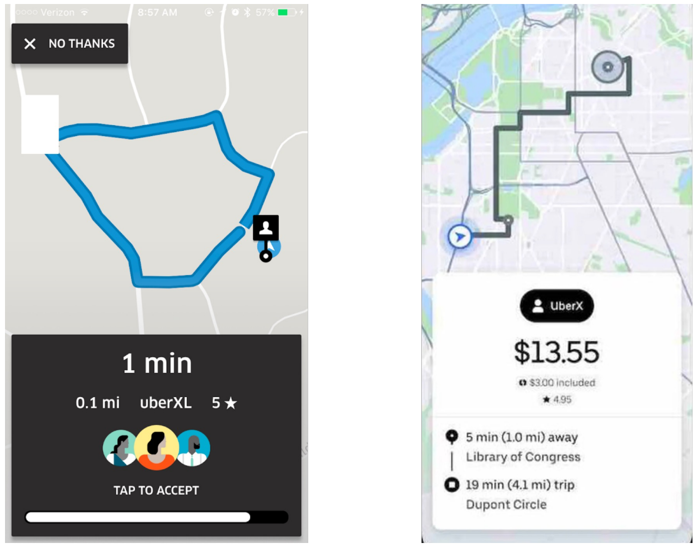


Figure 1: An Uber driver's app view when receiving a request. Left: before Upfront Fares (prior to 2022); right: after Upfront Fares

Note: The left side of the figure shows the pre-Upfront Fares interface, where drivers lacked access to specific pay details for rides. The right side illustrates the post-Upfront Fares model, providing drivers with upfront pay estimates.

forms. At first glance, the upfront quote model increases transparency by revealing the per-trip compensation; the increased transparency seems inherently beneficial for workers, as it provides them with more detailed information to make decisions. However, this intuition only holds if all other factors remain unchanged—a condition that is rarely met in practice. Transparency is deeply intertwined with other mechanisms, particularly pay policies, and changes in transparency often shift control dynamics between the platform and the workers in unintended ways.[1]

In fact, greater transparency can increase the platform's control. For workers to decide whether to work for a platform or accept a particular request, there have to be some form of agreement between the platform and the workers, even if it is not formalized as a traditional contract. This agreement, implicit or otherwise, is essential for ensuring workers have the necessary information and incentives to participate. When little to no information about specific requests is shared, as in the flat rate mechanism above, the platform is "forced" to make more robust commitments—such as a fixed commission rate—to provide workers with enough certainty to decide whether to join the platform. Without such commitments, workers would lack the necessary information to participate. By contrast, when the platform provides detailed information, such as job-specific pay through the upfront quote mechanism, it gains flexibility to adjust compensation at a granular level, aligning

[1]The literature (e.g. Romanyuk and Smolin 2019) has shown that excessive transparency in platform settings can lead to market failures, such as when workers engage in excessive cherry-picking, thereby reducing service levels and overall market efficiency. While these are important considerations, they are outside the scope of our analysis, which focuses on the interplay between information policies and pay structures under the assumption that demand does not depend on service levels. This allows us to isolate the effects of transparency and pay policies on worker and platform outcomes.

pay with its profit-maximizing objectives. This flexibility can reduce workers' control over their earnings, as they become more exposed to pay variability dictated by the platform's optimization.

These observations suggest that transparency is neither inherently good nor bad; rather, it is a lever whose effects depend on how it interacts with other factors, particularly pay policies. A nuanced understanding of these interdependencies is essential for evaluating the implications of transparency for both workers and platforms, motivating the central questions of this study.

This research analyzes the impact of information through the lens of these complexities. We examine two mechanisms, inspired by the real-world examples discussed earlier, and compare their implications for both workers and platforms. Specifically, we investigate how information policy and worker pay policy jointly shape outcomes. Furthermore, we characterize the platform's optimal design and explore alternative designs that could benefit workers. The next section summarizes our methodology and key findings.

1.1 Model overview and key results

We analyze a platform with two key levers: worker pay, represented by commission rates, and the information policy. The supply of workers is assumed to be perfectly elastic with a reservation wage of w_0, subject to a maximum worker cap $\bar{\lambda}$, which represents the upper limit of workers available to the gig economy. Demand is uncertain and is characterized by a set of demand scenarios. In each scenario, workers freely decide whether to join the platform. Those who enter form a queue to receive job assignments. Jobs are heterogeneous and belong to one of the two types: good and bad. The type of a job reflects its value or price, which corresponds to how much the platform charges the customer for the request. While the platform has full knowledge of job types, the extent to which this information is shared with workers is governed by the platform's information policy. We model the platform's information policy as a signal sent to workers for each request, with full details provided in Section 2.3. In summary, under a *full information* policy, the signal fully reveals the true type of the request, allowing workers to infer its actual value. Under a *no information* policy, the signal is identical for all requests, making it impossible for workers to distinguish between different types. The platform may also adopt a *partial information* policy, where some information about the request type is selectively disclosed.

Upon receiving a job, workers infer its type based on the information provided by the platform and decide whether to accept it by solving a utility maximization problem. These decisions, in turn, impact the platform's profitability. We then characterize the platform's optimal decisions regarding commission rates and information policies, and analyze their implications for workers. A complete description of the model setup can be found in Section 2.

Our results yield the following insights.

- *Full information generally benefits the platform, with a caveat.* We find that contrary to conventional wisdom, sharing more information is in fact beneficial for the platform, with an important premise that the platform must have the flexibility in adjusting the commission rate in the scenarios. With perfect flexibility, full information is the optimal information policy across all possible demand scenarios (Theorem 1). However, when the platform commits to one commission rate across demand scenarios, full information may backfire and lead to a lower profit than not sharing any information at all (Proposition 7). A typical situation where this could happen is when the demand distribution has peaks with a low probability of occurrence. To optimize for the aggregate profit, the platform tends to choose a commission rate that is "too high" under the peak demand to induce sufficient workers to serve demand. The high worker pay and the full information thus encourage workers to excessively cherry-pick under the low demand scenarios, leading to a lower aggregate profit for the platform compared with the no information policy.

The results suggest that sharing information can be a good strategy for the platform, but it is a delicate lever that requires careful execution from the platform. While a no information policy does not fully unlock the platform's ability to optimize its profit, it is more robust to demand uncertainty and does not require frequent updates to the worker pay. In contrast, the full information policy requires the worker pay to be properly chosen and adjusted according to the market conditions. This perhaps explains why many gig economy platforms started with a flat rate mechanims, i.e. a no information policy with a simple fixed pay rate, in its earlier phase.

- *More transparency is not equal to more control for workers.* While the upfront quote model provides workers with detailed, request-specific information, this transparency does not translate into greater control over their earnings. Instead, workers are worse off under this model compared to the flat rate mechanism (Proposition 5). The upfront quote model allows the platform to customize pay at a granular level, enabling it to strategically vary worker compensation based on demand scenarios. This enhanced flexibility enables the platform to extract more value from workers by aligning pay with its profit-maximizing objectives, often at the expense of worker utility. As a result, the platform is better off under the upfront quote model than the flat rate model (Proposition 3).

  The paradox lies in the apparent trade-off between transparency and control: although workers receive more information about their jobs, they lose the commitment from the platform over their earnings. The platform's ability to fine-tune pay diminishes workers' ability to leverage transparency for better decision-making, leaving them in a worse position despite having access to more information. This underscores the importance of analyzing transparency not in isolation but in conjunction with the mechanisms used to implement it, as increased information without careful policy design can diminish worker control and result in worse overall outcomes for workers. Therefore, regulations could inadvertently harm workers if transparency is the sole focus.

- *Information can be counterproductive to both the platform and workers, if the commission rate is fixed across various demand scenarios.* When the platform is unable to adjust its commission rate under a multiple demand scenario case, the workers' cherry-picking behavior may negatively affect social welfare. Interestingly, in such an environment, information may also be counterproductive, because providing no information may have the potential to simultaneously increase the platform and the workers' payoff, which we call "optimal information omission". This is because the workers' inclination to cherry-pick in a full-information scenario makes the platform unwilling to set a high commission rate. Therefore, it leads to a surprising result that providing less information ends up being optimal for both the platform and the workers. This contrasts with the case where platform has the commitment power to set the commission rate, where the platform can always benefit by adopting a full information policy.

1.2 Related literature

The paper is closely related to two streams of literature: worker's supply and incentives in the gig economy and information disclosure and design on platforms.

Worker supply and incentives in the gig economy: Several papers studying the gig economy, including the ride-sharing economy, have focused on the supply side. Zha, Yin, and Du 2017 introduces equilibrium models for labor supply behavior in a ride-sourcing market, examining surge pricing and finding that dynamic pricing generally benefits the platform and drivers with increased revenue. Sun, Wang, and Wan 2019 explores the impact of hourly income rates on labor supply among freelance drivers in ride-sharing platforms, using econometric methods to estimate participation and working-hour elasticities while addressing sample self-selection bias and endogeneity and finding that these elasticities are generally positive but decrease with driver heterogeneity. Lian, Martin, and Ryzin 2022 provides a theory of gig economies where workers are part of a shared labor pool used by multiple firms, with larger firms paying more than smaller ones to maintain a worker pool. Taylor 2018 investigates how delay sensitivity and agent independence influence the optimal per-service price and wage on an on-demand service platform. Similarly, Bai et al. 2019 characterizes the optimal price and wage rates that maximize the profit of the platform to coordinate endogenous demand with endogenous supply. Furthermore, related to our paper, which studies worker welfare, Benjaafar et al. 2022 investigates the impact of labor pool size and different types of wage-floor regulations on the welfare of independent workers on an on-demand service platform. Though our paper relates to the aforementioned papers by studying the platform's optimal strategies in gig economies, we differentiate by looking into their optimal strategy in both information disclosure and driver pay.

One of the key motivating examples in this paper is the ride-hailing industry. A growing body of literature examines driver pay and incentive structures in ride-hailing markets. Ma, Fang, and Parkes 2022 studies the design of a spatio-temporal pricing mechanism that ensures drivers are incentive-aligned, always accepting their dispatched trips rather than strategically relocating or waiting for better opportunities. Castro et al. 2021 investigates the design of queue-based dispatch mechanisms, showing that traditional FIFO dispatching can lead to cherry-picking behavior, and proposes randomized FIFO mechanisms to align incentives and improve efficiency. Afèche, Liu, and Maglaras 2023 analyzes the strategic behavior of ride-hailing drivers and explores how platforms can regulate the market through demand-side admission control and supply-side repositioning, demonstrating how these levers impact equilibrium performance. This literature typically assumes that drivers have full information about the pay of each request, whereas the role of information is the main focus of this paper.

Platform's Information Design: D. Zhu, Minner, and Bichler 2023 employs a queueing-theoretic approach to study how information disclosure about service delays impacts platform revenue and user behavior . Candogan and Strack 2023 explores the platform's optimal information policy regarding supplier quality to maximize revenue, highlighting mechanisms such as delayed disclosure and strategic obfuscation. They tackle a more general information design problem with multiple privately-informed agents, aiming to characterize the structure of optimal mechanisms without restricting the number of actions. Gur et al. 2023 focuses on optimal information disclosure in a setting with multiple privately informed agents interacting in a game. Boyaci, Chakraborty, and Gurkan 2024 explores a firm's optimal information strategy when launching a new product, considering heterogeneous consumer beliefs and the availability of external information. Their paper concentrates on the strategic communication of a firm to a market with diverse consumer segments and costly information acquisition, while our paper focuses on the operational aspects, including the information design and pay design of a gig-economy platform.

In particular, our paper consider the platform's information design that simultaneously affect the workers and consumers, which relates to the literature on information disclosure and design on two-sided platforms: Chu, Wan, and Zhan 2018 show that providing ride information to drivers may reduce drivers' equilibrium profit since the drivers may choose to take more profitable riders via "strategic idling". This is consistent with worker's "cherry-pick" behavior in our model. They propose a routing policy that can achieve the first-best outcome for ride-sharing systems. In contrast, we focus on studying the joint design of information and pay policies and their effects on both the platform and workers. Furthermore, we use the Bayesian persuasion framework, introduced by Kamenica and Gentzkow 2011, which has been widely adopted by platform design literature (Ashlagi, Monachou, and Nikzad 2021, Lingenbrink and Iyer 2019, Romanyuk and Smolin 2019). Moreover, Arora, Zheng, and Girotra 2024 examine the role of pooled transportation in mitigating ride-hailing congestion and emissions, demonstrating that operational improvements such as reducing walking distance to shuttle stops can be as effective as congestion surcharge policies. Their findings complement our study by illustrating how service design influences driver behavior and platform efficiency. B. Hu, M. Hu, and H. Zhu 2022 uses a two-period game-theoretic model to analyze the strategic behavior of riders and drivers with differing response times to surge pricing and identifies two distinct equilibrium pricing strategies: skimming and penetration pricing. Bimpikis, Papanastasiou, and Zhang 2024 examines a firm's optimal information strategy for a new product launch, considering heterogeneous consumer beliefs and the possibility of acquiring additional information. In a recent working paper by Sekar and Siddiq 2023, the joint design of information and commission fee in a two-sided platform is analyzed. However, our paper differs from theirs in two key aspects. First, our focus is the platform's information design to the gig workers where the demand scenarios may vary, while their focus is avoiding disintermediation from the online market. Second, our underlying uncertainty is the value of works, which is observed by the platform, while their uncertainty is the quality of the seller, which is also observed by the sellers themselves. Next, among this stream of literature, Romanyuk and Smolin 2019 is the most related one. They explore the dynamics of short-lived buyers and sellers within a platform environment. Their work illuminates that full information disclosure can potentially lead to market inefficiencies, and they suggest that the adoption of more generalized information policies can reestablish market efficiency. We differentiate in the following two dimensions. First, we add the dynamic commission rate, as opposed to the pure information design, in their paper; second, we examine the platform's optimal decision under further uncertainty in demand. Finally, there are empirical works that illustrate the significance of information disclosure in platforms (see Fatemipour, Madanizadeh, and Joshaghani 2020, and Rhee et al. 2022).

2 Model setup

In this section, we introduce our assumptions on the market and the key players. We then delve deeper into the decisions of the workers and the platforms. We conclude this section by presenting the equilibrium concept, main assumptions, and the sequence of events.

2.1 Market conditions and key players

We model the strategic interactions between a gig economy platform ("the platform") and a pool of labor supply ("the workers"). The platform matches the workers with job requests. More specifically, the platform has two operational levers: the worker pay, modeled as a commission rate, and the information policy, modeled as a signal sent by the platform. At the beginning of the decision horizon, the platform selects and commits to a set of worker pay and information policy; workers, upon observing the policy, decide whether to provide service and the acceptance strategies for the jobs. Next, we introduce the components of our model in detail.

2.1.1 Demand.

The demand is assumed to be uncertain and consists of N demand scenarios. In each scenario, job requests arrive in a Poisson process. The arrival rate of requests varies in each scenario. In the example of ride-hailing, the different scenarios can be thought of as different times of the day, with high-demand scenarios being the morning rush hour and the low-demand scenarios being midnight. We denote the arrival rate of requests in scenario j as μ_j and its probability mass as f_j, where $j = 1, ..., N$. Thus, $\sum_{i=1}^{N} f_j = 1$.

Furthermore, there is heterogeneity in the value of the requests. This value can be thought of as the price that the platform charges to the customer for fulfilling the request. Thus, a higher-value request generates more revenue for the platform. We model the value of the request as the *type* of a request and consider a parsimonious setting with binary types: good requests, denoted as G, and bad requests, denoted as B. We use parameter i to represent the type of a request, where $i \in \{G, B\}$. Moreover, the value of a type i request is denoted as v_i. A good request has a higher value than a bad request; that is, $v_G > v_B$. Finally, we assume that the proportion of the good and bad requests are b and $(1 - b)$, respectively.

Motivation for the two types of requests. The assumption of two types of requests in our model is motivated by empirical observations in the ride-hailing industry, where drivers exhibit clear preferences for certain locations over others. This differentiation can be attributed to various factors, such as higher demand, better safety, and greater likelihood of subsequent ride opportunities in preferred locations. Studies have shown that drivers strategically position themselves in high-demand areas, like city centers, to maximize their earnings and reduce waiting times. These intrinsic location-based preferences are not fully captured by the monetary compensation alone, necessitating the introduction of different request types to reflect the varying perceived values by drivers. Therefore, even if the platform ensures balanced pay rates, the additional utility derived from favorable locations remains a critical factor in driver decision-making, justifying the distinction between good and bad requests in our model. Such heterogeneity in the value of requests in the gig economy context has also been extensively discussed by Romanyuk and Smolin 2019, the main insights of which are that gig workers have an incentive to "cream skim" and only pick the requests with desirable types.

Importantly, the type of a request is known to the platform but unknown to the workers. The platform can decide the amount of information to share with the workers (its information policy), which we discuss in more detail below.

2.1.2 The platform.

The platform mediates transactions between the supply (workers) and the demand (requests) by two levers: the commission rate, which controls the proportion of value that the workers receive from completing a request, and the information policy, which controls the worker's "action space" when a request is dispatched. We introduce the two levers in detail below.

The commission rate. We assume that the platform adopts a commission rate model and pays the worker by a proportion of the request value. For example, under a commission rate of β, a worker earns βv_i for completing a request of type i. We denote the commission rate in scenario j as β_j and the commission rates for all scenarios as a tuple $\boldsymbol{\beta} = (\beta_1, \beta_2, ..., \beta_N)$, where $1 \leq \beta_j \leq 1,\ j = 1, 2, ..., N$.

We consider two possibilities for the commission rate:

- A single rate, where the commission rate is the same across all scenarios. That is, $\beta_1 = \beta_2 = ... = \beta_N$.
- A flexible rate, where the commission rate can be different across scenarios. That is, β_1, β_2, ..., β_N can be individually selected and vary from each other.

In both cases, the platform sets the rate(s) to maximize its profit.

The information policy. We start by formally defining the information policy and then discussing its implications. The platform's information policy is modeled as a signal sent by the platform to the workers for each request. In other words, when a worker receives a request, there is a signal associated with the request, which we denote as $\hat{i}$. Following Kamenica and Gentzkow 2011, we denote the set of the possible signals as $\mathcal{M}$. Then for signal $\hat{i} \in \mathcal{M}$, let $\sigma(\hat{i}|i \in \{G, B\})$ be the probabilistic distribution that the platform sends signal $\hat{i}$ when the type of a request is i. Naturally, for any type i, $\sum_{\hat{i} \in \mathcal{M}} \sigma(\hat{i}|i \in \{G, B\}) = 1$.

In general, the set of possible signals $\mathcal{M}$ can be arbitrarily large even for two types of requests, leading to a complicated analysis. However, we are able to show that all possible outcomes can be induced by a set of two signals, $\mathcal{M} = \{\mathcal{G}, \mathcal{B}\}$. We refer to signal $\mathcal{G}$ as the *good signal* and signal $\mathcal{B}$ as the *bad signal*. Moreover, we find that the information design is "one-sided", in the sense that a platform may disguise a bad request as a good one by sending a good signal, but never has an incentive to send a bad signal for a good request. Formally, we present the result in Lemma 1:

Lemma 1. *It is without loss of generality to make the following restrictions on information policy* σ.

- $\mathcal{M} = \{\mathcal{G}, \mathcal{B}\}$. *That is, a binary signal is sufficient.*
- $\sigma(\mathcal{B}|i = G) = 0$. *That is, the platform never sends a bad signal for a good request.*

Therefore, the information design is reduced to a single decision, i.e., how likely the platform will be truthful about the type of a bad request. We denote this probability as q and refer to it as the platform's information policy:

$$q = \sigma(\mathcal{B}|i = B)$$

A higher q implies more information shared with workers. When $q = 1$, the platform always sends a bad signal for a bad request, and the signal is perfectly consistent with the true type; when $q = 0$, the platform always sends a good signal for any type of request, and the signal is independent of the true type; when $0 < q < 1$, the platform sends a bad signal for a bad request with probability q, and the signal provides some indication of the true type. We refer to $q = 1$ as the *full information* policy, $q = 0$ as the *no information* policy, and q in between as the *partial information* policy.

By the Bayes rule, given an information policy q, there is a mapping between the type and the signal. For a bad signal,

$$P(B|\hat{i} = \mathcal{B}) = 1,\ P(G|\hat{i} = \mathcal{B}) = 0$$

For a good signal,

$$P(B|\hat{i} = \mathcal{G}) = \frac{(1-q)(1-b)}{b + (1-q)(1-b)},\ P(G|\hat{i} = \mathcal{G}) = \frac{b}{b + (1-q)(1-b)}$$

Based on these relationships, we can derive the arrival rates and the expected values of the two signals, which we summarize in Lemma 2:

Lemma 2. *Consider an information policy $q \in [0, 1]$ and signals $\hat{i} \in \{\mathcal{G}, \mathcal{B}\}$. Then for a demand scenario with demand rate μ, the expected arrival rates of the signals are given by*

$$\mu_{\mathcal{G}} = \mu(b + (1-q)(1-b)),\ \mu_{\mathcal{B}} = \mu(1-b)q \tag{1}$$

The expected values of the signals are given by

$$v_{\mathcal{G}} = \frac{bv_G + (1-q)(1-b)v_B}{b + (1-q)(1-b)},\ v_{\mathcal{B}} = v_B \tag{2}$$

Moreover, $bv_G + (1-b)v_B \leq v_{\mathcal{G}} \leq v_G$.

All else being equal, the value of the good signal $v_{\mathcal{G}}$ is increasing in the information policy q; that is, as more information is shared, fewer bad requests are mixed with good requests; as q approaches 1 which represents a full information policy, the value of the good signal approaches v_G, the value of the good request. Meanwhile, the arrival rate of the good signal $\mu_{\mathcal{G}}$ is decreasing in q, implying that fewer requests are signaled as good when more information is shared. As we show in Section 3, this creates tension for workers when deciding the set of requests to accept.

2.1.3 Workers.

Workers are independent contractors and can freely enter and exit the platform. Workers know the platform's policy $(\boldsymbol{\beta}, q)$ and choose their strategies accordingly. In each demand scenario, workers arrive at the platform following a Poisson process and form a queue to receive requests. The queueing process is discussed in more detail in Section 2.2. Moreover, we assume that there is a maximum number of workers available to provide service, which we denote as $\bar{\lambda}$ and refer to as the *size of the worker pool*. The worker supply is assumed to be perfectly elastic with a reservation wage w_0, provided that it is below $\bar{\lambda}$. That is, in any scenario, workers continue to enter the platform until the expected hourly earnings are no longer at or above w_0, or the size of the pool $\bar{\lambda}$ has been reached.

Conditional on entering the platform, workers decide which type(s) of requests to accept, with the objective of maximizing the utility. More specifically, the worker utility is defined as

$$U = \beta v_A - w_0(W_A + \tau) \tag{3}$$

where β represents the worker commission rate, v_A represents the average value of the requests accepted by workers, W_A represents the average waiting time the worker spent in the queue, and τ represents the average request duration. That is, on average, workers earn βv_A for a request, at the cost of spending time W_A in waiting and time τ in completing it. Note that, v_A and W_A are both subject to the worker's acceptance strategy: when the workers are more selective about the requests, it increases the average value v_A; however, it also increases the waiting time W_A because workers have to wait longer for a specific type of requests. The optimal worker strategy should strike a balance between the value and the waiting cost.

It is worth noting that the feasible worker strategies are influenced by the platform's information policy. When the platform shares more information on the requests, workers are able to fine-tune the strategy. For example, if the platform shares no information ($q = 0$), then good and bad requests are indistinguishable to the workers; from the worker's perspective, there is only one type of request, with value $v_A = bv_G + (1-b)v_G$, i.e., the average value across all requests. In contrast, if the platform shares full information, workers have additional feasible strategies, such as only accepting good requests.

2.2 The worker's decision

As stated above, the worker's decision involves two steps, whether to provide service, and whether to accept a request. We first discuss the acceptance strategy under an exogenous arrival rate λ; then we derive the equilibrium arrival rate. Because workers are assumed to enter and exit the market instantaneously according to the earnings they receive, equilibria over time are decoupled, and it is sufficient to independently analyze the equilibrium within each given hour and demand scenario j. Thus, we focus the analysis on a single scenario and omit the subscript j whenever there is no ambiguity.

Acceptance strategy. As stated in Section 2.1, workers arrive at the platform in a Poisson process and wait in a queue for requests. At the top of the queue, they receive a request with signal $\hat{i} \in \{\mathcal{G}, \mathcal{B}\}$. If they accept the request, then they leave the queue and spend time τ to complete the request; if not, they remain in the queue and continue waiting. We denote the worker acceptance strategy as a tuple (x, y), where x represents the fraction of good signals acceptable to the workers, and y represents the fraction of bad signals acceptable to the workers. Then for a given (x, y), all acceptable requests arrive in a Poisson process with rate $(x\mu_{\mathcal{G}} + y\mu_{\mathcal{B}})$, where $\mu_{\mathcal{G}}$ and $\mu_{\mathcal{B}}$ are the arrival rates of the good and bad signals, respectively, defined in Lemma 2.

Therefore, the waiting process is an M/M/1 queue; for worker arrival rate λ, the waiting time (the total time a worker spends in the system) is given by

$$W_A = \frac{1}{(\mu_A - \lambda)^+}$$

where μ_A represents all requests acceptable to the workers. In other words,

$$\mu_A = x\mu_{\mathcal{G}} + y\mu_{\mathcal{B}}, \tag{4}$$

Moreover, the average value from all acceptable requests is given by

$$v_A = \frac{x\mu_{\mathcal{G}}}{\mu_A} v_{\mathcal{G}} + \frac{y\mu_{\mathcal{B}}}{\mu_A} v_{\mathcal{B}} \tag{5}$$

where $v_{\mathcal{G}}$ and $v_{\mathcal{B}}$ are defined in Lemma 2 and represent the expected value of the good and bad signal, respectively. Hence, following the worker's utility (3), given the worker arrival rate λ and the platform's policy in a scenario (β, q), the worker solves the following problem:

$$\max_{x,y\in[0,1]} U = \beta v_A - w_0 \left(W_A + \tau\right), \text{ where } W_A = \frac{1}{(\mu_A - \lambda)^+} \tag{6}$$

We denote the optimal utility from Eq. (6) as $U(\lambda, \beta, q)$.

Equilibrium arrival rate. Recall that workers are perfectly elastic, with a maximum supply of $\bar{\lambda}$ (the size of the worker pool). Without the limit of the pool size, then workers will continue to join the platform until the utility reaches zero. In particular, let $\lambda^*(\beta, q)$ denote the (unconstrained) maximum worker arrival rate such that $U(\lambda, \beta, q) = 0$. Then for any arrival rate $\lambda > \lambda^*(\beta, q)$, the waiting cost is too high and the utility is negative. As a result, workers will start to exit the platform until the utility is back to zero. Hence, $\lambda^*(\beta, q)$ is the equilibrium worker arrival rate, provided an unlimited worker pool[2]. Therefore, with the size of the worker pool $\bar{\lambda}$, the equilibrium arrival rate is given by

$$\lambda(\beta, q) = \min\{\lambda^*(\beta, q), \bar{\lambda}\} \tag{7}$$

Note that $\lambda(\beta, q)$ implicitly depends on the demand arrival rate in that the waiting time is a function of μ_A; thus, we sometimes parameterize λ with a subscript j for the equilibrium arrival rate in scenario j to avoid ambiguity.

2.3 The platform's decision

The platform maximizes the *aggregate profit* by selecting its commission rate and information policy $(\boldsymbol{\beta}, q)$. Denote the profit in scenario j as $\pi_j(\beta, q)$. Then the aggregate profit is the sum of the profit from all scenarios, weighted by the probability mass. That is,

$$\pi(\boldsymbol{\beta}, q) = \pi(\beta_1, ..., \beta_N, q) = \sum_{j=1}^{N} f_j \cdot \pi_j(\beta_j, q) \tag{8}$$

In each scenario, the profit π_j depends on two main factors: the profit margin, and the number of requests completed. Both factors have important relationships with the worker strategy, which we discuss below.

Profit margin. The profit margin of a request is determined by both the commission rate and the value of the request. Since the workers ultimately decide which requests to accept, the latter is directly determined by the worker strategy. Thus, given a platform strategy (β, q), the average profit margin of all acceptable requests is then $(1 - \beta)v_A$, where v_A is given by Eq. (5) and is a function of (β, q). Hence, when workers are more selective about the requests (e.g. only accepting the good signal), it has a positive effect on the platform as well: if the supply is limited, then prioritizing more valuable requests also improves the platform's profit margin. This indicates that sharing more information with the workers can potentially be beneficial.

Number of successful requests. The number of successful transactions, on the other hand, critically depends on the worker's strategy. The queueing process described in Section 2.2 impacts the platform's operations in several ways: if a request arrives but is unacceptable to the workers, the request will be lost; if an acceptable request arrives, but no worker is available in the queue to accept it, the request will also be lost. Additionally, the average time required to complete a request, $(W_A + \tau)$, plays a crucial role in determining the number of jobs that can be completed within a given time period. Specifically, if workers spend more time waiting (W_A) or working (τ)

[2] Depending on the policy (β, q), it is possible to have $U(0, \beta_j, q) \leq 0$, i.e. even when no worker is in the queue, the utility is non-positive. In this case, $\lambda^*(\beta, q) = 0$.

on each request, the total number of shifts workers can perform in a day is reduced, limiting the platform's throughput.

Combining these factors, the platform's profit in scenario j is formally defined as:

$$\pi_j(\beta, q) = (1-\beta)v_A \cdot \frac{\lambda_j(\beta, q)}{W_A + \tau}, \tag{9}$$

where v_A represents the average value of the acceptable requests (defined in Eq. (5)), and $\lambda_j(\beta, q)$ represents the equilibrium worker arrival rate in scenario j (defined in Eq. (7)). The denominator, $W_A + \tau$, accounts for the average time each worker spends in the system per job, which limits the number of shifts workers can complete in a fixed operating period. Together, $\lambda_j(\beta, q)/(W_A + \tau)$ represents the platform's effective throughput of completed jobs.

From the platform's perspective, optimizing the profit in a scenario involves balancing two competing forces: the margin effect (term $(1-\beta)v_A$) and the throughput effect (term $\frac{\lambda_j(\beta,q)}{W_A+\tau}$). Increasing β improves worker participation, captured by $\lambda_j(\beta, q)$, but reduces $(1-\beta)$, negatively impacting the margin. Furthermore, the implications of β and q on v_A and $(W_A + \tau)$ require precise characterization of the worker strategy. In Section 3, we provide detailed results on the worker strategy and discuss its influence on the platform's strategy.

This setup then allows us to analyze the platform's decision under the two mechanisms of interest: the flat rate, and the upfront quote. Below, we introduce the mathematical definitions of the two mechansims.

Definition 1 (Flat Rate)**.** *Under the flat rate mechanism, the platform adopts a no-information policy ($q = 0$) and selects a single commission rate that applies uniformly across all scenarios. Formally, the platform solves the following optimization problem:*

$$\max_{0 \le \beta_1, \ldots, \beta_N \le 1} \sum_{j=1}^{N} f_j \cdot \pi_j(\beta_j, 0) \qquad\qquad s.t.\ \beta_1 = \beta_2 = \cdots = \beta_N$$

Since workers receive no information about individual jobs under this mechanism, their action space is limited to either accepting all jobs or rejecting all jobs.[3] However, the commitment to a single commission rate provides a degree of predictability and stability for workers.

Definition 2 (Upfront Quote)**.** *Under the upfront quote mechanism, the platform adopts a full-information policy ($q = 1$) and selects individual commission rates for each scenario (flexible rate).*

[3]Technically, workers could reject jobs randomly, but this strategy is dominated by either accepting all or rejecting all.

Formally, the platform solves the following optimization problem:

$$\max_{0\leq\beta_1,\ldots,\beta_N\leq 1} \sum_{j=1}^{N} f_j \cdot \pi_j(\beta_j, 1)$$

Under this mechanism, workers have full information about each job, knowing exactly how much they will be compensated.[4] This transparency can encourage workers to cherry-pick jobs to maximize their utility. At the same time, the platform gains flexibility in setting pay by tailoring commission rates to specific demand scenarios, eliminating the commitment required under a single commission rate.

2.4 Assumption, and sequence of events, and equilibrium concept

In this section, we provide additional information about the model setup and a summary of the events.

Assumption. Throughout the paper, we assume that demand is thick enough, such that the platform can make a positive profit without being too strategic about its information policy. Formally, we assume that:

Assumption 1 (Viability of the market)**.** *The platform can make a positive profit in any demand scenario when not sharing any information with the workers (i.e. q=0). That is,*

$$\mu_j \geq \frac{1}{\bar{v}/w_0 - \tau}, \ \forall j \tag{10}$$

and

$$\bar{v} > w_0\tau \tag{11}$$

where $\bar{v} = bv_G + (1-b)v_B$ *and represents the average value across all requests.*

In other words, Assumption 1 requires the demand arrival rates to be sufficiently large, such that the platform can survive by using a no information policy – the "default" information policy adopted by major US ride-hailing platforms like Uber and Lyft prior to 2022. Moreover, the average value of the requests should be sufficient to cover the workers' reservation earnings for completing the request, otherwise no worker is willing to provide service. Nevertheless, the workers may still need to be strategic about which requests to accept in order to break-even, because $\bar{v}$ does not necessarily cover the cost of waiting in the queue.

[4]Under the upfront quote mechanism, the platform is assumed to apply the same commission rate to all requests within the same demand scenario. While the platform could potentially gain more profit by setting different commission rates for different types of jobs, our results provide a lower bound on the platform's profit for this class of mechanisms.

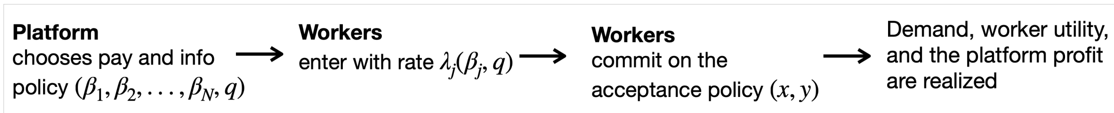


Figure 2: The sequence of events

Sequence of events. Combining all components in the model, the sequence of events is illustrated by Fig. 2. The model is solved backward, starting with a single demand scenario and the worker's acceptance strategy, treating the platform policy and the worker arrival rate as exogenously given. Then for a given platform policy, the worker's equilibrium arrival rate is derived. We then look into the implications of $\boldsymbol{\beta}$ and q in each scenario and derive the optimal platform strategy.

Equilibrium concept. Following Kamenica and Gentzkow 2011, the equilibrium concept considered in this model is the sender-preferred (platform-preferred) subgame perfect equilibrium. That is, whenever the worker is indifferent between two actions, the platform can induce its preferred action, i.e., accepting a request rather than rejecting it.

3 Worker strategy

In this section, we characterize the worker's optimal strategy, given the platform's information policy q and the commission rates $\boldsymbol{\beta}$. Since a worker can freely choose whether to participate and which requests to accept in each demand scenario, we analyze the worker's decision in one demand scenario. For brevity, throughout Section 3, we omit the subscript j and use μ to represent the demand arrival rate.

A worker has two decisions to make. A worker first decides whether to enter the market; then conditional on entering, a worker decides which subset of requests to accept. In Section 3.1, we first characterize the worker's acceptance strategy, treating the arrival rate λ as exogenous given; then in Section 3.2, we discuss how the equilibrium arrival rate changes as a function of the platform's decisions, as well as the resulting acceptance strategy as a function of the platform's decisions, taking into account the equilibrium arrival rate.

3.1 Analysis under an exogenous arrival rate λ

The following proposition characterizes the worker's optimal acceptance strategy that maximizes the worker utility Eq. (6), for a given λ:

Proposition 1. *Consider a scenario with demand rate μ. Then given a commission rate β and an information policy q, as well as a worker arrival rate $\lambda > 0$, the optimal worker acceptance strategy to* (6) *satisfies the following:*

(i) Workers always accept requests with the good signal. That is, $x^* = 1$.

(ii) As λ *increases, workers accept more requests with the bad signal. That is,* y^* *is increasing in* λ.

(iii) The total rate of acceptable requests, μ_A^*, *is increasing in* λ *and can be characterized in closed-form:*

$$\mu_A^* = \begin{cases} \mu_{\mathcal{G}} & \text{if } \lambda < \mu_{\mathcal{G}} \cdot \varphi(\beta) \\ \lambda/\varphi(\beta) & \text{if } \mu_{\mathcal{G}} \cdot \varphi(\beta) \leq \lambda < \mu \cdot \varphi(\beta) \\ \mu & \text{if } \lambda \geq \mu \cdot \varphi(\beta) \end{cases} \tag{12}$$

where $\varphi(\beta)$ *is a strictly increasing function of* β *and is given by* $\varphi(\beta) = 1 - 1/\sqrt{\beta(v_G - v_B)\mu b/w_0}$.

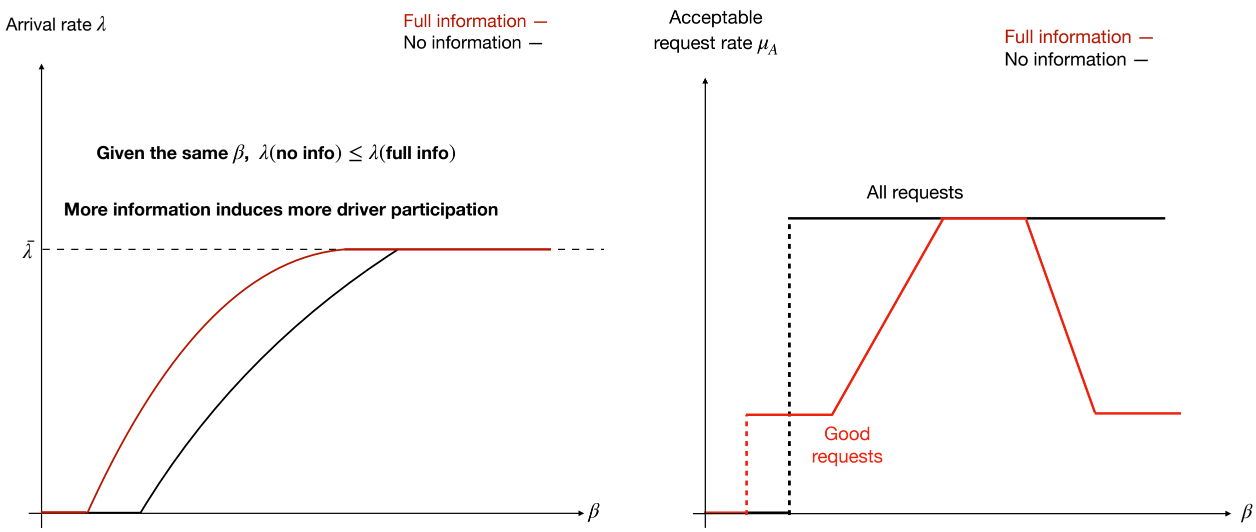
Proposition 1 fully characterize the worker's optimal acceptance strategy, given the platform's decisions and the worker arrival rate. Proposition 1 shows that, in any scenario, workers never have an incentive to reject a request with the good signal. Thus, workers mainly strategize over requests with bad signals. Proposition 1 then shows that, workers reject fewer requests with the bad signal, when there are more workers (higher λ). This result is intuitive – under a higher λ, workers compete with each other for jobs, and the average waiting time is higher; as a result, it is more expensive for workers to reject a job since they need to wait longer for the next job.

Finally, Proposition 1 characterizes the closed-form solution of μ_A^*, the total rate of acceptable jobs. Recall that $\mu_{\mathcal{G}}$ and $\mu_{\mathcal{B}}$ are defined by Eq. (1) and represent the arrival rate of the good and bad signals, respectively. They are both functions of the platform's information policy q. With more information (a higher q), fewer bad requests are disguised as good signals, i.e. $\mu_{\mathcal{G}}$ is decreasing in q, and $\mu_{\mathcal{B}}$ is increasing in q. When $q = 0$ (i.e. no information), $\mu_{\mathcal{G}} = \mu_G$, implying that all requests have the same signal and are non-distinguishable by workers. In this case, Proposition 1 implies that all requests will be accepted by workers, and $\mu_A^* = \mu$ is constant. Nonetheless, under any other information policy, Proposition 1 shows that as λ increases, μ_A^* is increasing, and workers reject fewer requests.

All else being equal, we say workers cherry-pick less when μ_A is higher. Formally, define:

Definition 3 (Cherry-Picking Behavior)**.** *Workers are said to engage in cherry-picking if* $\mu_A < \mu$ *and* $\lambda > 0$. *That is, workers participate in the gig economy (*$\lambda > 0$*) but selectively accept only a subset of all available jobs, resulting in* $\mu_A < \mu$.

Hence, Proposition 1 shows that under no information ($q = 0$), workers never cherry-pick; when $q > 0$, workers cherry-pick more when there are fewer workers. Building on Proposition 1, Section 3.2 presents the equilibrium worker arrival rate λ^* and the resulting worker acceptance strategy.



(a) The equilibrium arrival rate $\lambda(\beta, q)$ as a function of the commission rate β, under full information ($q = 1$) and no information ($q = 0$).

(b) The set of the requests acceptable to the workers, as a function of the commission rate β, under full information and no information.

Figure 3: Illustration of worker strategy as a function of the commission rate β.

3.2 Equilibrium arrival rate and cherry-picking

In this section, we present results on the equilibrium arrival rate, as well as the corresponding worker acceptance strategy.

Proposition 2. *Consider a scenario with demand rate μ. Given a commission rate β and an information policy q, the equilibrium worker participation rate $\lambda(\beta, q)$ satisfies the following:*

(i) The equilibrium arrival rate, $\lambda(\beta, q)$, is weakly increasing in both β and q. That is, a higher commission rate or greater transparency encourages worker participation.

(ii) Given q, workers exhibit non-monotonic cherry-picking behavior with respect to β. More precisely, as β increases, workers may first cherry-pick less (when $\lambda(\beta, q) < \bar{\lambda}$), and then cherry-pick more (when $\lambda(\beta, q) = \bar{\lambda}$).

The results are illustrated in Figure 3.

Proposition 2 summarizes the impact of the two levers of the platform, the commission rate and the information policy, on the equilibrium worker strategies. Proposition 2 shows that the platform can increase its worker supply $\lambda(\beta, q)$ by either passing over more value (through a higher β) or more information (through a higher q) to the workers.

Proposition 2 then reveals a more nuanced result on how (β, q) influences the worker's acceptance strategy. Illustrated by Fig. 3b, workers started by accepting only the requests with a good signal. As β increases, workers start to be less selective and accept more bad requests. This happens when β is relatively small, and the resulting equilibrium arrival rate $\lambda(\beta, q)$ is small as well. The intuition is that, in this region, β induces more worker participation; the increase in $\lambda(\beta, q)$ leads to longer waiting time, which discourages workers from cherry-picking. However, as β further increases, till the point where $\lambda(\beta, q) = \bar{\lambda}$, the worker supply is saturated, and a higher β can no longer induce more workers. In this case, a higher β increases the value of a good request, encouraging the workers to cherry-pick more.

Combining both results, Proposition 2 reveals interesting insights on how information and worker pay jointly influence the worker strategy: while sharing request information may induce workers to cherry-pick, such cherry-picking behavior can be controlled by the lever of worker pay. When the commission rate is properly chosen, workers may accept all requests and not cherry-pick at all even under full information. In addition, more information helps with inducing more workers, which is another force that discourages cherry-picking. These results suggest that the platform may benefit from a full information policy, providing that the commission rate β is carefully chosen.

Next, in Section 4, we introduce the platform's decisions and its implication on workers.

4 Main results

In this section, we present the main results.

4.1 Optimal mechanism for the platform

Our first result characterizes the platform's optimal information policy, when the commission rate β can be fully chosen by the platform in each demand scenario. We find that, in this case, full information is the optimal information policy. Theorem 1 formalizes this result:

Theorem 1. *Consider a profit-maximizing platform that jointly optimizes the commission rate $\boldsymbol{\beta} = (\beta_1, \beta_2, \ldots, \beta_N)$ and the information policy q. Then in each scenario j, the optimal information policy is full information ($q = 1$). That is,*

$$\pi_j(\beta_j^*(1), 1) \geq \pi_j(\beta_j^*(q), q), \text{ for all } q \tag{13}$$

where $\beta_j^*(q) \in \arg\max_\beta \pi_j(\beta, q)$. Moreover, $\beta_j^*(q)$ is weakly decreasing in q.

Theorem 1 states that contrary to the common belief, full information is in fact optimal in all demand scenarios, providing that the commission rate β_j in each scenario is chosen to maximize the profit. This outcome is the result of balancing several competing forces. A critical insight underpinning this result is the platform's ability to set β, which ensures that worker utility is zero in equilibrium, as workers are supplied perfectly elastically up to the participation cap $\bar{\lambda}$. This equilibrium condition leads to a surprising neutrality: the term $\frac{\beta v_A}{W_A + \tau}$, representing the cost per hour paid to workers, is constant across all information policies, fixed at the workers' reservation wage w_0. Consequently, given β, the trade-offs between job value (v_A) and efficiency (via waiting time W_A) cancel out, and the platform's profit depends solely on maximizing worker participation λ.

Full information dominates because it results in a higher worker arrival rate (λ) compared to no information. As shown in Proposition 2 of Proposition 2, for a fixed β, λ is higher when more information is disclosed (i.e. higher q). Under full information, workers adopt a richer strategy, selectively accepting jobs based on their value. This selectivity aligns with the platform's objectives: by improving v_A, workers' cherry-picking behavior directly increases the platform's profit. The neutrality result demonstrates that the improvement in v_A fully offsets any loss of efficiency from increased waiting time, as long as β is sufficiently low to maintain zero worker surplus. In contrast, under no information, workers lack visibility into individual job values, reducing their strategy to a binary decision of accepting or rejecting all jobs. This limitation leads to a lower equilibrium utility for workers at any given λ, discouraging participation compared to full information.

Recall that the goal of this analysis is to compare the flat rate and upfront quote mechanisms. The flat rate mechanism restricts the platform to select a single commission rate, whereas the upfront quote mechanism allows the commission rate to vary across scenarios. Under the same information policy, the optimal aggregate profit under a single commission rate cannot exceed that under a flexible commission rate. Combined with Theorem 1, this leads to the following result:

Proposition 3. *The upfront quote mechanism (Definition 2) always results in weakly higher profit for the platform compared to the flat rate mechanism (Definition 1). Formally,*

$$\sum_j f_j \pi_j(\beta_j^*(1), 1) \geq \sum_j f_j \pi_j(\beta^*, 0), \tag{14}$$

where $\beta_j^*(1) \in \arg\max_\beta \pi_j(\beta, 1)$ *represents the profit-maximizing commission rate in scenario* j *under the upfront quote mechanism and* $\beta^* \in \arg\max_\beta \sum_j f_j \pi_j(\beta, 0)$ *represents the optimal single commission rate under the flat rate mechanism.*

As discussed earlier, while full information enables workers to be more selective in the jobs they accept, the platform's control over the commission rate β ensures that worker surplus remains zero in equilibrium. This control allows the platform to fully offset the efficiency loss caused by increased cherry-picking with the corresponding improvement in the average job value v_A. Consequently, full information benefits the platform as long as the commission rate β_j can be adjusted flexibly, as permitted by the upfront quote mechanism. In other words, when pay is flexible, transparency amplifies this positive effect, leading to higher platform profits under the upfront quote mechanism compared to the flat rate policy.

Having examined the implications of the two mechanisms for the platform, we now turn to their impact on workers. This analysis is presented in Section 4.2.

4.2 Impact on the workers

The following Proposition 4 shows the impact of the commission rate on the worker utility:

Proposition 4. *Under a single demand scenario j, given information policy q, the profit-maximizing commission rate $\beta_j^*(q)$. Then there are two cases:*

(i) $\pi(\beta_j^*(q), q) \leq 0$*. That is, the market is not viable under information policy q.*

(ii) $\pi(\beta_j^*(q), q) > 0$*. Then under $\beta_j^*(q)$, the worker utility $U(\lambda(\beta_j^*(q), q), \beta_j^*(q), q) = 0$.*

Proposition 4 shows that under profit-maximizing commission rate $\beta_j^*(q)$, the worker's utility is always zero. Therefore, for the workers, we find that while upfront quote allows workers to be more strategic in accepting jobs, the platform's control over the commission rate dominates the benefit from information, leading to a worse outcome for the workers:

Proposition 5. *Consider a profit-maximizing platform that makes the optimal decision for its commission rates. Then workers are always worse off under the upfront quote mechanism than under the flat rate mechanism. Moreover, this relationship is strict when there is a demand peak with a high demand rate and low probability mass. One set of such conditions for a two-scenario setting is characterized below:*

$$\mu_1 \leq \mu_2 - \bar{\lambda}, \tag{15}$$

$$f_1 > \frac{\pi_2(\beta_2^*(0), 0) - \pi_2(\beta_1^*(0), 0)}{\pi_1(\beta_1^*(0), 0) + \pi_2(\beta_2^*(0), 0) - \pi_2(\beta_1^*(0), 0)}, \tag{16}$$

where $\beta_j^*(0) \in \arg\max_\beta \pi_j(\beta, 0)$ *for* $j = 1, 2$.

Hence, even though workers gain more information under upfront quote, they are worse off due to the control gained by the platform from upfront quote. The platform's control under the upfront quote mechanism allows it to tailor the commission rate to maximize its profit in each demand scenario. This flexibility enables the platform to reduce the pay in high-demand scenarios, capturing a larger share of the surplus generated by an increased number of jobs and worker participation. While all else being equal, workers benefit from more information under upfront quote, this benefit is dominated by the platform's ability to adjust β, which keeps workers' equilibrium utility at zero. In particular, when there is a demand peak characterized by high demand rates and low probability mass, the platform can exploit these conditions to extract more surplus, leaving workers strictly worse off than under the flat rate mechanism, where the commission rate is uniform and does not adapt to demand fluctuations.

5 Extension: A single commission rate and optimal information omission

In Section 4, it has been shown that a flexible pay rate, combined with full information, results in worse outcomes for workers. This deterioration is attributable to the platform being afforded excessive control over the pay mechanism. Weakening such control might improve the welfare of the workers. Thus, the regulator is inevitably considering whether restricting to a single pay rate could benefit the workers. Therefore, we limit the platform's flexibility in the pay mechanism by restricting it to a single commission rate across all demand scenarios. Our goal is to focus on how different information policies affect the platform and the driver's payoff. The conventional wisdom is that full information policy is better than no information policy. Although this is still true for some cases, we find interesting cases in which no information may simultaneously benefit the platform and the workers.

In this section, we start by presenting sufficient conditions under which no-information policies dominate full-information policies from the platform's perspective. Under such a parameter space, we then present cases where the workers also benefit from being provided no information. Finally, we explain the underlying effects that lead to this dominance of no information. We show that under a single rate, full information can still be optimal, but it is weakly dominated by the no-information policy under a broad set of conditions (Proposition 6). Under the above weak dominance conditions, if the demand pattern has a peak with a low probability of occurrence, then full information is strictly dominated by no information (Proposition 7). Workers may also get hurt when both single rate and full information policy are enforced (Proposition 9). In sum, information outperforms full information when the demand is highly volatile and the platform cannot update its rate in each scenario. In the rest of the section, we present the precise characterization of the conditions where the platform and the workers benefit from no information policy.

5.1 The platform's problem: no information can dominate full information

Although full information dominates no information when the platform can freely adjust pay across demand scenarios, it is no longer the case under the single rate mechanism. In this section, we present two conditions under which full information is dominated by no information. The first condition is a weak dominance condition, where no information performs at least equally good as full information. Without loss of generality, we consider two demand scenarios, μ_1 and μ_2, where $\mu_1 < \mu_2$.[5] We start by presenting the **weak dominance condition**.

[5]This simplification is for ease of exposition. Similar results can be found when extended to multiple demand scenarios.

Lemma 3. *Given any demand scenario j and the commission rate β, if*

$$\delta \leq \frac{1}{\mu_j b \tau} v_B, \tag{17}$$

where δ represents the value difference between good and bad requests, i.e. $\delta = v_G - v_B$, then

(i) No information is weakly better than full information, i.e., $\pi_j(\beta, 0) \geq \pi_j(\beta, 1)$.

(ii) There exists $\hat{\beta}_j$ such that no information is strictly better than full information for $\beta \in (\hat{\beta}_j, 1)$.

(iii) The worker's utility under no information is greater than 0 for $\beta \in (\hat{\beta}_j, 1)$, i.e., $U(\lambda(\beta, 0), \beta, 0) > 0$.

The condition (17) is a key condition, which requires that the good rides and bad rides are close enough in their values. Alternatively, as long as the demand μ_j is high enough under scenario j, then this condition is also satisfied. The intuition is that when rides are close enough in values, cherry-picking can be counterproductive to both the platform and the workers. No information yields weakly higher profit under any commission rate, and a strictly higher profit and a higher driver utility for sufficiently high commission rates. To explain this, as β increases, the worker pool increases in size until it satiates. When there are relatively fewer workers in the market, cherry-picking is overall beneficial to the platform; however, once it satiates, cherry-picking will negatively impact the platform's objective. Fig. 4a provides an graph illustration of Lemma 3. Fig. 4a shows that when the commission rate β is below the threshold $\hat{\beta}_j$, no information and full information generates the same platform's profit. When $\beta \in (\hat{\beta}_j, 1)$, no information clearly generates higher profit.

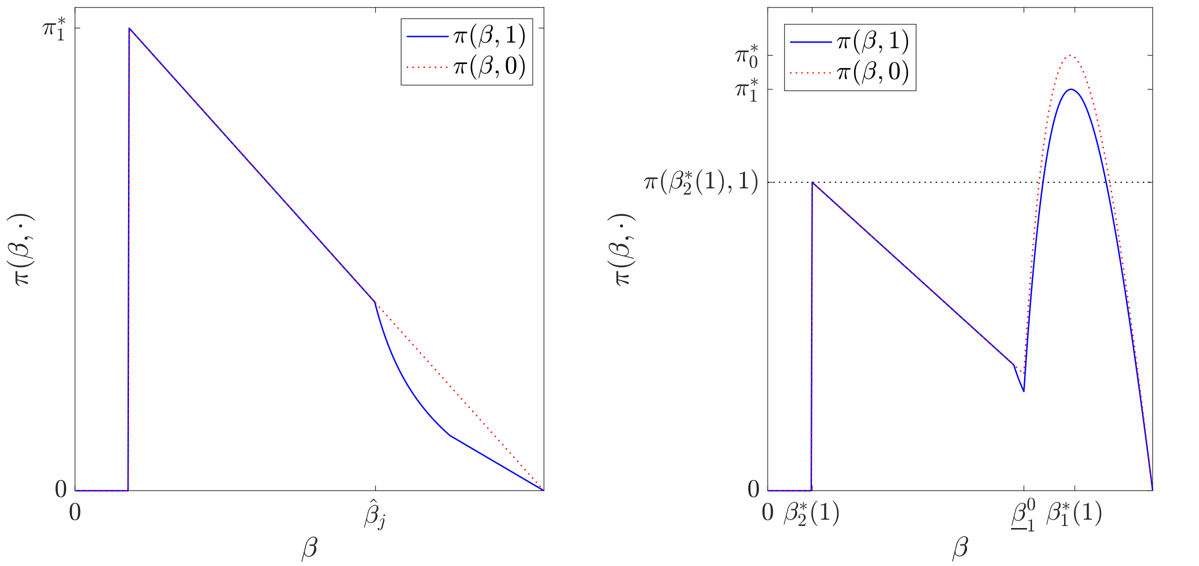
An immediate implication of Lemma 3 and Theorem 1 is:

Corollary 1. *Under a single demand scenario j, if condition Eq.* (17) *holds, then the platform's optimal profit is the same under full information and no information. That is,* $\max_\beta \pi_j(\beta, 1) = \max_\beta \pi_j(\beta, 0)$.

Furthermore, Lemma 3 leads to the following proposition by considering the aggregate profit from multiple demand scenarios:

Proposition 6. *Suppose there are two demand scenarios, μ_1 and μ_2. Suppose both μ_1 and μ_2 satisfy Eq.* (17)*. Then no information leads to weakly higher aggregate profit than full information for the platform.*

The weak dominance results prepare us to show the second set of conditions, under which no information strictly dominates full information. Next, in Proposition 7, we introduce a set of **strong dominance conditions**, under which no information leads to strictly higher profit than full information:



(a) Example: no information weakly dominates full information for any β.

(b) Example: no information strictly dominates full information.

Figure 4: Illustrations of profit outcomes under different information policies.
Note: Parameters for Fig. 4a: $\mu_j = 2.3$, $v_G = 1$, $v_B = 0.7522$, $w_0 = 0.1$, $\tau = 0.5$, $\bar{\lambda} = 0.1$, and $b = 0.3$. $\max_\beta \pi(\beta, 0) = \max_\beta \pi(\beta, 1) = \pi_1^*$. Parameters for Fig. 4b: $\mu_1 = 0.2$, $\mu_2 = 2.3$, $f_1 = 0.99$, $v_G = 1$, $v_B = 0.7522$, $w_0 = 0.1$, $\tau = 0.5$, $\bar{\lambda} = 0.1$, and $b = 0.3$.

Proposition 7. *Consider a profit-maximizing platform that makes the optimal commission rate decision. Suppose the demand arrival rates in both scenarios satisfy Eq.* (17)*. Then the aggregate profit defined by Eq.* (8) *is strictly higher under no information than full information, provided that the demand distribution has a demand peak with a sufficiently low probability. In other words,*

$$\max_\beta \pi(\beta, 1) < \max_\beta \pi(\beta, 0), \tag{18}$$

when μ_1 is low with a sufficiently high probability mass f_1. One set of such conditions is given by

$$\mu_1 < \frac{1}{\frac{1}{1-\bar{\lambda}/\mu_2}\frac{\bar{v}}{b\mu_2\delta} - \tau}, \tag{19}$$

$$f_1 > \frac{\pi_2(\beta_2^*(1), 1) - \pi_2(\beta_1^*(1), 1)}{\pi_1(\beta_1^*(1), 1) + \pi_2(\beta_2^*(1), 1) - \pi_2(\beta_1^*(1), 1)}, \tag{20}$$

where $\beta_j^*(1) \in \arg\max_\beta \pi_j(\beta, 1)$ for $j = 1, 2$.

In the following, we explain the rationale behind the conditions in Proposition 7 and provide some managerial insights. First, we define

$$\underline{\beta}_1^0 := \frac{w_0}{\bar{v}}\left(\frac{1}{\mu_1} + \tau\right), \tag{21}$$

which can be verified to be the lowest commission rate to make the market of demand scenario μ_1 viable, i.e., $\underline{\beta}_1^0 = \inf\{\beta|\lambda(\beta,1) > 0\}$. Next, recall Lemma 3, under demand scenario μ_2, there exists $\hat{\beta}_2$ such that $\pi_2(\beta,0) > \pi_2(\beta,1)$ for $\beta \in (\hat{\beta}_2, 1)$. Condition Eq. (19) guarantees that $\underline{\beta}_1^0 > \hat{\beta}_2$. Hence, the platform's aggregate profit can be expressed as

$$\begin{aligned}\pi(\beta,1) &= f_1\pi_1(\beta,1) + (1-f_1)\pi_2(\beta,1) \\ &= \begin{cases} (1-f_1)\pi_2(\beta,1), & \text{for } \beta \le \underline{\beta}_1^0, \\ f_1\pi_1(\beta,1) + (1-f_1)\pi_2(\beta,1), & \text{for } \beta > \underline{\beta}_1^0, \end{cases}\end{aligned} \tag{22}$$

which implies that $\beta_2^*(1) = \arg\max_{\beta \le \underline{\beta}_1^0} \pi(\beta,1)$ since $\beta_2^*(1)$ is the optimal commission rate if the platform only faces demand scenario μ_2. Furthermore, condition Eq. (20) guarantees that $\pi(\beta_1^*(1),1) > \pi(\beta_2^*(1),1)$ and implies that $\beta_1^* > \underline{\beta}_1^0$, where $\beta_1^* \in \arg\max_\beta \pi(\beta,1)$. Therefore,

$$\max_\beta \pi(\beta,0) \ge \pi(\beta_1^*,0) = f_1\pi_1(\beta_1^*,0) + (1-f_1)\pi_2(\beta_1^*,0) > f_1\pi_1(\beta_1^*,1) + (1-f_1)\pi_2(\beta_1^*,1) = \pi(\beta_1^*,1)$$

where the second inequality follows from Lemma 3 and $\underline{\beta}_1^0 > \hat{\beta}_2$. Fig. 4b provides a graph illustration of the above discussion.

Recall that μ_1 is the arrival rate of the demand in the low-demand scenario, and f_1 represents the likelihood that a low-demand scenario occurs. The proposition says that when the low demand scenario is sufficiently low but occurs frequently enough, no information will generate a higher expected payoff than full information. Notice that in this scenario, the platform chooses a high commission rate β. Yet, the cherry-picking behavior will become more pronounced when the demand is high. When the platform can flexibly adjust the commission rate, it will suppress workers' cherry-picking by selecting a (reasonably) low commission rate; however, when the platform lacks the ability to change the commission rate, it has to settle for a high commission rate such that it is sufficiently profitable under the lower demand scenario. Thus, cherry-picking leads to a negative overall effect on the platform, and the full information policy, which encourages cherry-picking, is dominated by the no information policy.

5.2 Impact on the workers

The last subsection has shown that the platform can be worse off under a full information policy. In this subsection, we further take the worker's utility into consideration. In a two-demand environment, we construct a set of conditions such that no information yields a higher payoff to both the platform and the workers.

Proposition 8. *Consider a profit-maximizing platform that makes the optimal commission rate decision. Suppose the demand arrival rates in both scenarios satisfy Eq.* (17)*. Then, both the platform's aggregate profit and the worker's utility are weakly higher under no information than full*

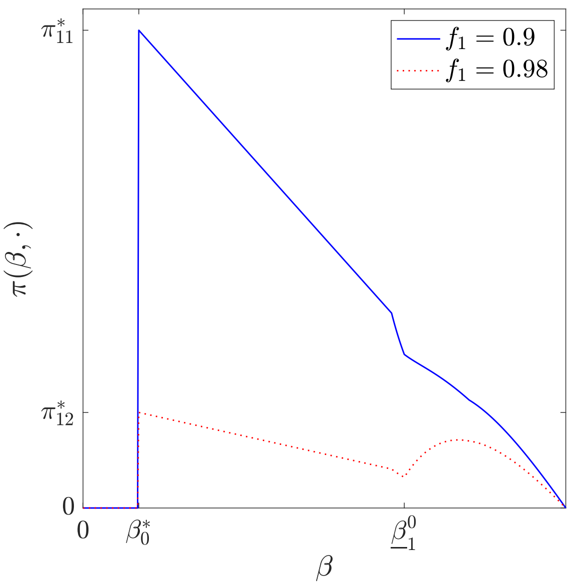


Figure 5: An illustration of Proposition 8. Parameters: $\mu_1 = 0.2$, $\mu_2 = 2.3$, $v_G = 1$, $v_B = 0.7522$, $w_0 = 0.1$, $\tau = 0.5$, $\bar{\lambda} = 0.1$, and $b = 0.3$. $\pi^*_{11} = \max_\beta \pi(\beta, 1)$ when $f_1 = 0.9$ and $\pi^*_{12} = \max_\beta \pi(\beta, 1)$ when $f_1 = 0.98$.

information when the following conditions are satisfied

$$\mu_1 \le \mu_2 - \bar{\lambda}, \tag{23}$$

$$\pi(\beta_2^*(1), 1) > \max_{\beta \ge \underline{\beta}_1^0} \pi(\beta, 1), \tag{24}$$

where $\beta_j^*(1) \in \arg\max_\beta \pi_j(\beta, 1)$ *for* $j = 1, 2$ *and* $\underline{\beta}_1^0$ *is defined in Eq.* (21)[6].

Proposition 8 shows that under a set of mild conditions, no information weakly dominates full information in terms of both the platform's profit and the worker's utility. Similar to the discussion below Proposition 7, condition Eq. (23) guarantees that $\underline{\beta}_1^0 > \beta_2^*(1)$. As a result, the platform's aggregate profit under full information can also be expressed by Eq. (22). Hence, if the condition Eq. (24) also holds, then the platform's optimal commission rate is $\beta_2^*(1)$, which is the same as the optimal commission rate when the platform only faces demand scenario μ_2 and leads to a non-viable demand scenario μ_1. Therefore, following Proposition 4, the worker's utility is zero under full information. Combined with Proposition 6, both the platform's profit and the worker's utility are weakly higher under no information than full information. Fig. 5 provides a graph illustration of Proposition 8. We find that as long as f_1 is small enough, the peak of the aggregate profit function left to $\underline{\beta}_1^0$ is higher than any value that is right to $\underline{\beta}_1^0$. Fig. 5 also shows that with other parameters being well chosen, the range of f_1 that satisfies Eq. (24) can be large.

[6]It is worth noting here that condition Eq. (23) is weaker than condition Eq. (19).

Finally, we provide an analytical result that shows that no information can strictly dominate full information in terms of both the platform's profit and the worker's utility.

Proposition 9. *Consider a profit-maximizing platform that makes the optimal commission rate decision. Suppose the demand arrival rates in both scenarios satisfy Eq.* (17) *and Eq.* (19)*. Then, there exists a range of* f_1 *such that both the platform's aggregate profit and the worker's utility are strictly higher under no information than full information.*

In the following, we describe how to find the desirable range of f_1. Following our discussion on Fig. 5 and profit function Eq. (22), as f_1 increases, the difference between the peak of the aggregate profit function left to $\underline{\beta}_1^0$ ($\max_{\beta \leq \underline{\beta}_1^0} \pi(\beta, 1)$) and the peak right to $\underline{\beta}_1^0$ ($\max_{\beta > \underline{\beta}_1^0} \pi(\beta, 1)$) becomes smaller. Hence, there exists f_1^* such that if $f_1 = f_1^*$, then $\max_{\beta \leq \underline{\beta}_1^0} \pi(\beta, 1) = \max_{\beta > \underline{\beta}_1^0} \pi(\beta, 1) + \epsilon$ for any small enough ϵ. As a result, $\beta_2^*(1) = \arg\max_\beta \pi(\beta, 1)$ and the worker's utility is zero under full information.

For no information, since condition Eq. (19) guarantees that $\underline{\beta}_1^0 > \hat{\beta}_2$, we have $\max_{\beta > \underline{\beta}_1^0} \pi(\beta, 0) > \max_{\beta > \underline{\beta}_1^0} \pi(\beta, 1)$, where the inequality follows from Lemma 3 and $\underline{\beta}_1^0 > \hat{\beta}_2$. Hence, if ϵ is small enough, we have $\max_{\beta > \underline{\beta}_1^0} \pi(\beta, 0) > \max_{\beta \leq \underline{\beta}_1^0} \pi(\beta, 1) = \max_\beta \pi(\beta, 1) = \max_{\beta \leq \underline{\beta}_1^0} \pi(\beta, 0)$, where the last equality follows from Corollary 2. The above inequality further implies that the optimal commission rate under no information is greater than $\hat{\beta}_2$. Following Lemma 3(iii), the worker's utility is greater than zero under no information. Therefore, the platform's aggregate profit and worker's utility are strictly higher under no information than full information. Fig. 6 provides a graph illustration of the above discussion.

5.3 Discussion: optimal information omission

In the previous two subsections, we have shown interesting results of *optimal information omission*. That is, under a single rate, a no-information policy has the potential to simultaneously improve the platform and the worker's welfare. This leads to a drastic difference from the baseline model under a flexible commission rate, where full information is always optimal for the platform.

The fact that a no-information policy leads to a better outcome than full information for both the platform and workers can be explained by the "prisoner's dilemma" between the platform and the workers. Notice that if the workers do not cherry-pick, the platform is willing to provide a high commission rate β, because of the existence of another demand scenario μ_1, which is a Pareto optimal outcome for both parties. However, once provided more information, the worker would prefer to cherry-pick, which increases their own payoff but undermines the platform's profit due to a lower utilization rate. Anticipating this, the platform turns to providing a lower commission rate. In short, workers would be better off if they could have committed to not cherry-picking. But their inability to do so harms their own welfare. This is a typical example demonstrating that having fewer options sometimes makes the worker's life better.

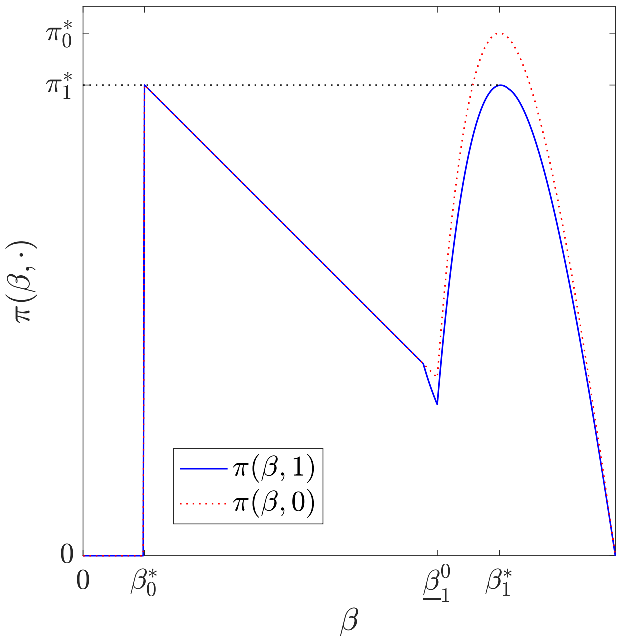


Figure 6: An illustration where no information strictly dominates full information. Parameters: $\mu_1 = 0.2$, $\mu_2 = 2.3$, $f_1 = 0.9866$, $v_G = 1$, $v_B = 0.7522$, $w_0 = 0.1$, $\tau = 0.5$, $\bar{\lambda} = 0.1$, and $b = 0.3$. $\beta_0^* = \arg\max_\beta \pi(\beta, 0)$ and $\beta_1^* = \arg\max_\beta \pi(\beta, 1)$.

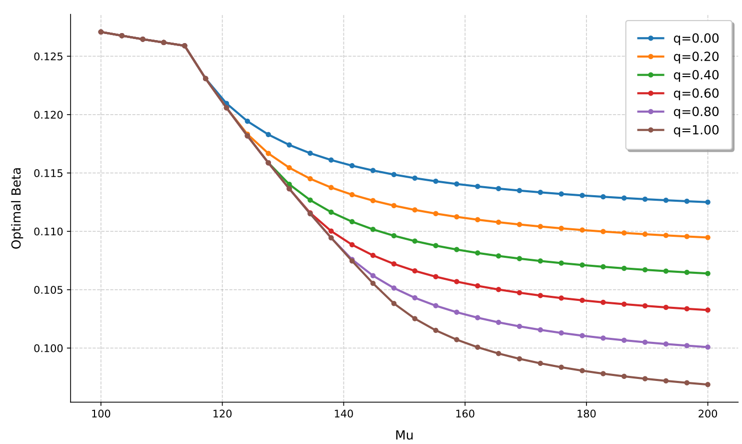


Figure 7: Impact of information level q on optimal commission rate β_q^* across varying μ values. Parameters: $v_G = 80$, $v_B = 20$, $w_0 = 15.0$, $\tau = 0.5$, $\bar{\lambda} = 100$, and $b = 0.8$.

To illustrate how the absence of information can benefit the platform under a single commission rate, we begin by presenting a figure that depicts how optimal commission rates vary across different demand scenarios. Fig. 7 illustrates the relationship between the optimal commission rate, the information policy q, and the demand rate μ.

One can observe that given μ the optimal commission rate β_q^* is decreasing in q, illustrating the substitutability effect. When examining the impact of the demand rate μ on the optimal β, the common trend is that the commission rate paid to the workers decreases as the demand rate increases. Such a direction makes intuitive sense: all else being equal, when the jobs arrive more frequently, workers have less down time and are willing to work at a lower rate. Interestingly, Fig. 7 also shows that sharing more information leads to a more "variable" optimal commission rate across demand scenarios. When the demand rate μ is low, all information policies lead to the same optimal commission rate; as μ increases, β_q^* decreases at a faster speed with a higher q than a lower q. At the right end of the axis, $\beta_{q=1}^* = 0.097$ and $\beta_{q=0}^* = 0.113$, leading to about 17% of difference.

That more information induces a larger variation in the optimal commission rate is closely related to the workers' response to different amounts of information. Under no information, workers have a limited action space (accepting all or rejecting all), and therefore their acceptance strategies remain the same as long as their utility is non-negative. In contrast, when workers have full information about the requests, their strategy is ultra-sensitive to the platform's commission rate and can be significantly more variable than the no information case, which is also illustrated by Fig. 3b. Therefore, when external factors such as the demand rate change, the platform has to update its strategy in a more agile way. However, if the platform is constrained in its ability to adjust pay across demand scenarios, it hurts more under full information than no information. This explains the result that no information dominates full information in the following section. The key effect that leads to optimal information omission is the cherry-picking effect, where the workers cherry-pick the rides when provided information on the value of the rides. Since it reflects the interesting dynamics between the platform and the workers, we discuss it in detail below.

Recall that there are three driving forces in the platform's profit: the margin effect, which improves the platform's profit as the workers get pickier about the requests; the utilization effect, which reduces the platform profit as the workers waste more time waiting for acceptable requests; and the supply effect, which has a less clear relationship with the worker strategy and may go to either direction depending on the parameters.

Fig. 8 illustrates the comparison of the platform profit under full and no information, as a function of the commission rate β. As shown in Fig. 8, as β increases, the comparison between no and full information evolves in different directions. This reflects the interplay among the forces:

- When β is low (Region 1), the worker supply is low as well. There are more jobs relative to

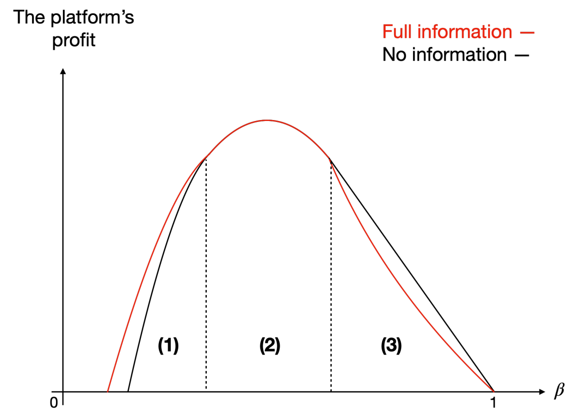


Figure 8: The platform's profit, as a function of β, under no and full information

Note: Region (1): Full information dominates no information; (2): Full and no information lead to identical profit; (3) No information dominates full information. Note that in this figure, the optimal profits under no and full information are identical, which is a special case and does not hold in general.

workers. As a result, waiting (the utilization effect) has little impact on the profit, and cherry-picking does not significantly reduce the utilization. Therefore, the value effect dominates the waiting effect, and full information outperforms no information.

- In contrast, when β is high (Region 3), the worker supply is high as well. The deterioration in utilization waiting is more pronounced. As a result, cherry-picking leads to a significant waste of worker hours for the entire system, which cannot be compensated by the gain from the margin. Hence, no information outperforms full information.
- When β is intermediate (Region 2), full and no information leads to identical profit. In this region, workers choose to accept all requests even under full information, i.e. cherry-picking is not attractive for the workers.

Going back to Lemma 3, when the condition Eq. (17) holds, it eliminates Region (1). In other words, it characterizes a setting where the utilization effect is pronounced across the board, and the platform's loss from low utilization cannot be offset by the gain from a higher margin. This explains why Lemma 3 ensures no information to be at least as good as full information.

6 Conclusion

This paper studies the optimal decision of a gig economy platform with two operational levers: the worker pay and the information policy. We find that under the joint optimization of both levers, full information is the optimal information policy. While more information encourages workers to be more selective and reject more requests, it also induces more workers to provide service and allows higher margin requests to be prioritized. The positive effect from supply and margin outweighs the negative effect from utilization, provided that the commission rate is properly chosen.

Furthermore, we show that when the platform is unable to update its commission rate based on demand scenarios, the no-information policy may dominate the full-information policy for both the platform and the workers. Under a single commission rate, the no-information policy achieves at least as good as full information when the increased margin from worker cherry-picking is limited. Moreover, if the demand distribution has a peak with a low probability of occurrence, then the no-information policy strictly dominates the full-information policy. The result implies that full information may not be as robust as no information amid demand uncertainty.

Our results reveal a striking potential downside to regulators' push for greater transparency: while transparency may appear beneficial, it can leave workers worse off if it leads to a shift from a flat rate to a per-request quoted rate. Moreover, our analysis shows that such a shift in the pay mechanism may be unavoidable, as platforms risk losing profit without flexibility under a more transparent market. Ultimately, the cost of transparency is borne by the workers. This insight is consistent with stylized facts from the ride-hailing market, where drivers for Uber and Lyft have reported lower and more volatile earnings following the introduction of upfront pay policies (Kerr 2022). Thus, our findings yield insights on the recent regulatory change towards a more transparent gig economy market: while transparency appears desirable to the workers, it may come at the cost of more volatility in the pay rate; workers may indeed be worse off compared to the simple "status quo" mechanism, with no information and a single rate.

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Appendices

Proof of Lemma 1, Part 1

Proof. Proof. We first prove the first part of Lemma 1. Let the posterior belief after observing a message m be $p_m = P(i = G|m)$. We show a monotonicity result where if a driver accepts a message that induces posterior p_{m2}, then he also accepts p_{m1} for $p_{m1} > p_{m2}$. If $m_2 \in A$, then $m_1 \in A$. Suppose not, notice that $V_A = \sum_m \mu_m(v_G p_m + v_B(1-p_m))$, which is an increasing function in p_m. Define a new acceptance set such that $\mu'_{m_1} = \mu_{m_1} + \epsilon$ and $\mu'_{m_2} = \mu_{m_1} - \epsilon$ for an arbitrarily large $\epsilon > 0$ keeps μ_A a constant, while increases v_A, which increases the driver's expected payoff. Therefore, following Theorem 1 in Bergemann and Morris 2016, it is without loss of generality to consider a signal space with the same dimensionality of the action space, which is binary. Let $\{\mathcal{G}, \mathcal{B}\}$ be the two signals. Without loss of generality, let $p_{\mathcal{G}} \geq p_{\mathcal{B}}$. By monotonicity, $\mathcal{G} \in A, \mathcal{B} \notin A$. Next, we show $\sigma(\mathcal{B}|i = G) = 0$. That is $p_{\mathcal{B}} = 0$. Suppose not and let $p_{\mathcal{B}} > 0$. Since $\mu_{\mathcal{B}} = \mu_G\sigma(\mathcal{B}|i = G) + \mu_B\sigma(\mathcal{B}|i = B)$, let's define a new information policy σ' where $\sigma'(\mathcal{B}'|i = G) = 0$ and $\sigma'(\mathcal{G}'|i = G) = \sigma(\mathcal{G}|i = G)$. By Bayes' rule, $p_{\mathcal{G}'} > p_{\mathcal{G}}$ and hence $\mathcal{G}' \in A$. In the meantime, $\mu_{G'} > \mu_G$, which means the new policy leads to a higher acceptance rate of rides, generating a higher profit for the platform. We delay the proof of the next half till later.

Because we consider binary signal, define the signal as (q, r) where $q = \sigma(\mathcal{B}|i = B)$ and $r = \sigma(\mathcal{B}|i = G)$. By Bayes' rule, the posterior beliefs are $P(i = G|\hat{i} = \mathcal{G}) = b(1-r)/(b(1-r) + (1-b)(1-q))$ and $P(i = G|\hat{i} = \mathcal{B}) = br/(br + (1-b)q)$. Define the expected value of the ride, conditional on signal $\hat{i} = \mathcal{G}, \mathcal{B}$ be $v_{\mathcal{G}} = v_G P(i = G|\hat{i} = \mathcal{G}) + v_B(1 - P(i = G|\hat{i} = \mathcal{G}))$ and $v_{\mathcal{B}} = V_G P(i = G|\hat{i} = \mathcal{B}) + V_B(1 - P(i = G|\hat{i} = \mathcal{B}))$. Next, we propose the following lemma for expressions of $\mu_{\mathcal{G}}$, $\mu_{\mathcal{B}}$, $v_{\mathcal{G}}$ and $v_{\mathcal{B}}$.

□

Lemma 4. *Consider an information policy $q, r \in [0, 1]$ and its corresponding requests with signal $\hat{i} \in \{\mathcal{G}, \mathcal{B}\}$. Then the expected arrival rates of the signals are given by*

$$\mu_{\mathcal{G}} = \mu[b(1-r) + (1-b)(1-q)], \;\; \mu_{\mathcal{B}} = \mu[br + (1-b)q] \tag{25}$$

The expected values of the signals are given by

$$v_{\mathcal{G}} = \frac{b(1-r)v_G + (1-q)(1-b)v_B}{b(1-r) + (1-q)(1-b)}, \;\; v_{\mathcal{B}} = \frac{brv_G + (1-b)qv_B}{br + (1-b)q} \tag{26}$$

Next, we make the following assumption that $v_{\mathcal{G}} \geq v_{\mathcal{B}}$, which requires that $1 \geq q \geq r \geq 0$, which is without loss of generality.

With a slight abuse of notation, we now define the value function from equation (6) to be $U(\lambda, \beta, q, r)$, in order to emphasize its relationship to r. Next, we derive the driver's acceptance strategy with the following proposition.

Proposition 10. *Given an information policy (q, r), commission rate β, and worker arrival rate λ, the optimal solution to (6) can be characterized based on the value of λ:*

1. *If $\lambda \leq \tilde{\lambda}_1(\beta, q, r)$, then the worker only accepts the good signals. Moreover, $\mu_A = \mu_{\mathcal{G}}$, $x^* = 1$, and $y^* = 0$.*
2. *If $\tilde{\lambda}_1(\beta, q, r) < \lambda < \tilde{\lambda}_2(\beta, q, r)$ and $\phi(\beta, q, r) \geq 1$, then the worker accepts all good signals and part of the bad signals. Moreover, $\mu_A = \lambda(1 + \frac{1}{\sqrt{\phi(\beta, q, r)} - 1})$, $x^* = 1$, and $y^* = \frac{\mu_A - \mu(b(1-r) + (1-q)(1-b))}{\mu[br + (1-b)q]}$.*
3. *If $\lambda \geq \tilde{\lambda}_2(\beta, q, r)$, then the worker accepts all signals. That is, $\mu_A = \mu$, $x^* = 1$, and $y^* = 1$.*

where

$$\tilde{\lambda}_1(\beta, q, r) := \mu\,[b(1-r) + (1-b)(1-q)]\left(1 - 1/\sqrt{\phi(\beta, q, r)}\right), \tag{27}$$

$$\tilde{\lambda}_2(\beta) := \mu\left(1 - 1/\sqrt{\phi(\beta, q, r)}\right), \tag{28}$$

and

$$\phi(\beta, q, r) := \frac{\beta(v_{\mathcal{G}} - v_{\mathcal{B}})\mu(b(1-r) + (1-b)(1-q))}{w_0} = \frac{\mu b(1-b)\beta(q-r)(v_G - v_B)}{w_0(br + (1-b)q)}.$$

Proposition 10 can be easily generalized from Proposition1. Next, we propose the following lemma of partial derivatives for future uses. Since they are straightforward, we omit the proofs here. As r increases, the bad ride's expected value will increase, and the good ride's expected value will decrease. Furthermore, there will be less good rides, and the expected value of accepted rides will decrease. The following technical lemma shows derivations that will be used in future proofs.

Lemma 5.

$$\frac{\partial v_{\mathcal{B}}}{\partial r} = \frac{b(1-b)q(v_G - v_B)}{(br + (1-b)q)^2} > 0.$$

$$\frac{\partial v_{\mathcal{G}}}{\partial r} = -\frac{b(1-b)(1-q)(v_G - v_B)}{(b(1-r) + (1-b)(1-q))^2} < 0.$$

$$\frac{\partial \mu_{\mathcal{G}}}{\partial r} = -\mu b < 0.$$

$$\frac{\partial v_A}{\partial r} = \frac{qb(1-b)(v_G - v_B)}{(br + (1-b)q)^2}\left[1 - \frac{\mu}{\lambda}(1 - \frac{1}{2\sqrt{\phi(\beta, q, r)}})\right].$$

The next two lemmas are two monotonicity results that will later be useful to show that the platform will optimally choose $r = 0$.

Lemma 6. *Fix any β, q, $U(\lambda, \beta, q, r)$ and $\lambda(\beta, q, r)$ are non-increasing in r.*

Proof of Lemma 6: First, notice that $\mu_{\mathcal{G}}$ is decreasing in r, $\mu_{\mathcal{B}}$ is increasing in r, $v_{\mathcal{G}}$ is decreasing in r, $\mu_{\mathcal{B}}$ is increasing in r. Next, we show that $U(\lambda, \beta, q, r)$ is decreasing in r. To consider the monotonicity of $U(\lambda, \beta, q, r)$ in r, we discuss the three cases in Proposition 10. First, if $\lambda \leq \tilde{\lambda}_1(\beta, q, r)$, the driver accepts only good rides. Hence $U(\lambda, \beta, q, r) = \beta v_{\mathcal{G}} - w_0\left(\frac{1}{\mu_{\mathcal{G}} - \lambda} + \tau\right)$. Notice that $\frac{\partial U(\lambda,\beta,q,r)}{\partial r} = \beta \frac{\partial v_{\mathcal{G}}}{\partial r} + w_0 \frac{1}{(\mu_{\mathcal{G}} - \lambda)^2} \frac{\partial v_{\mathcal{G}}}{\partial r} < 0$. The inequality comes from Lemma 5. Now, discuss the second case. Next, we focus on the second case in Proposition 10 with an interior solution of λ.

$$\frac{\partial U(\lambda, \beta, q, r)}{\partial r} = \frac{\partial[\beta v_A - w_0(W_A + \tau)]}{\partial r} = \frac{\beta q b(1-b)(v_G - v_B)}{(br + (1-b)q)^2}[1 - \frac{\mu}{\lambda}(1 - \frac{1}{\sqrt{\phi(\beta, q, r)}})] \leq 0 \tag{29}$$

The last inequality comes from the fact that $\lambda \leq \mu\left(1 - 1/\sqrt{\phi(\beta, q, r)}\right)$ in Proposition 10. For the third case, if $\lambda \geq \tilde{\lambda}_2(\beta)$, then the worker accepts all rides. Then $U(\lambda, \beta, q, r) = \beta(bv_G + (1-b)v_B) - w_0(\frac{1}{\mu - \lambda} + \tau)$, which is not a function of r. Hence, $\frac{\partial U(\lambda,\beta,q,r)}{\partial r} = 0$. Concluding the aforementioned three cases, $U(\lambda, \beta, q, r)$ is non-increasing in r. By arguments in Lemma 9, we have $U(\lambda, \beta, q, r)$ is strictly decreasing in λ. By definition of λ^*, we have $U(\lambda^*(\beta, q, r), \beta, q, r) = 0$. Consider $r_1 > r_2$, then notice that $U(\lambda^*(\beta, q, r_2)(\beta, q, r), \beta, q, r_1) \leq U(\lambda^*(\beta, q, r_2)(\beta, q, r), \beta, q, r_2) = 0$, it has to be that $\lambda^*(\beta, q, r_1) \leq \lambda^*(\beta, q, r_2)$. Furthermore, by definition that $\lambda(\beta, q, r) = \min\{\lambda^*(\beta, q, r), \bar{\lambda}\}$, we have $\lambda(\beta, q, r)$ is non-increasing in r. □

Lemma 7. *If $\lambda(\beta, q, r) = \bar{\lambda}$, then the principal's profit first decreases in r, then increases in r.*

Proof of Lemma 7: For the principal's profit, since $\lambda(\beta, q, r) = \bar{\lambda}$, we only need to look at $\frac{v_A}{W_A + \tau}$.

Since $\phi(\beta, q, r)$ decreases in r, we have $\tilde{\lambda}_1(\beta, q, r)$ and $\tilde{\lambda}_2(\beta, q, r)$ decrease in r. As r increases, the driver's acceptance policy changes from Scenario 1, then Scenario 2, and finally Scenario 3 (following Proposition 10).

Scenario 1: Driver only accepts good rides. Hence,

$$\frac{v_A}{W_A + \tau} = \frac{v_{\mathcal{G}}}{\frac{1}{\mu_{\mathcal{G}} - \lambda} + \tau}.$$

Since $v_{\mathcal{G}}$ and $\mu_{\mathcal{G}}$ decreases in r, we have $\frac{v_A}{W_A + \tau}$ decreases in r.

Scenario 2: Driver accepts good rides and some bad rides. Before we proceed to the proof, we present the following useful derivations:

$$\frac{\partial \phi(\beta, q, r)}{\partial r} = \frac{-\beta(v_G - v_B)\mu b(1-b)q}{w_0(br + (1-b)q)^2} < 0 \tag{30}$$

$$\frac{\partial v_{\mathcal{B}}}{\partial r} = \frac{b(1-b)q(v_G - v_B)}{(br + (1-b)q)^2} = -\frac{\partial \phi}{\partial r}\frac{w_0}{\mu\beta} \tag{31}$$

In scenario 2, we have

$$\begin{aligned} v_A &= \hat{x}^* v_{\mathcal{G}} + (1-\hat{x}^*)v_{\mathcal{B}} = \frac{\mu_{\mathcal{G}}}{\bar{\lambda}}\left(1 - \frac{1}{\sqrt{\phi}}\right)(v_{\mathcal{G}} - v_{\mathcal{B}}) + v_{\mathcal{B}} \\ &= \frac{\mu b(1-b)(q-r)(v_G - v_B)}{br + (1-b)q}\frac{1}{\bar{\lambda}}\left(1 - \frac{1}{\sqrt{\phi}}\right) + v_{\mathcal{B}} = \phi\frac{w_0}{\beta} \end{aligned} \tag{32}$$

$$\frac{\partial W_A}{\partial r} = \frac{1}{2\bar{\lambda}}(\phi)^{-1/2}\frac{\partial \phi}{\partial r} \tag{33}$$

Following (32), we have

$$\frac{\partial v_A}{\partial r} = \frac{\partial \phi}{\partial r}\frac{w_0}{\beta}\frac{1}{\bar{\lambda}}\left(1 - \frac{1}{\sqrt{\phi}}\right) + \phi\frac{w_0}{\beta}\frac{1}{2\bar{\lambda}}(\phi)^{-3/2}\frac{\partial \phi}{\partial r} + \frac{\partial v_{\mathcal{B}}}{\partial r} \tag{34}$$

Hence, following (33) and (34), we have

$$\frac{\partial[v_A/(W_A+\tau)]}{\partial r} = \frac{1}{W_A+\tau}\frac{\partial v_A}{\partial r} - \frac{v_A}{(W_A+\tau)^2}\frac{\partial W_A}{\partial r} \tag{35}$$

$$= \frac{1}{W_A+\tau}\frac{\partial \phi}{\partial r}\frac{1}{\bar{\lambda}}\left[\frac{w_0}{\beta}\left(1 - \frac{1}{\sqrt{\phi}}\right) + \frac{w_0}{2\beta}(\phi)^{-1/2} - \bar{\lambda}\cdot\frac{w_0}{\beta\mu} - \frac{v_A}{2(W_A+\tau)}(\phi)^{-1/2}\right] \tag{36}$$

and the term in the bracket is

$$\frac{w_0}{\beta}\left[1 - \frac{\bar{\lambda}}{\mu} - \frac{1}{2\sqrt{\phi}}\left(1 + \frac{v_A\beta}{(W_A+\tau)w_0}\right)\right] =: f(r) \tag{37}$$

and $f(r)$ has the same sign with

$$g(r) := \left(1 - \frac{\bar{\lambda}}{\mu}\right)\cdot 2\sqrt{\phi} - \left(1 + \frac{v_A\beta}{(W_A+\tau)w_0}\right). \tag{38}$$

Furthermore, we have

$$\begin{aligned} g'(r) &= \left(1 - \frac{\bar{\lambda}}{\mu}\right)\frac{\partial \phi}{\partial r}(\phi)^{-1/2} - \frac{\beta}{w_0}\frac{\partial[v_A/(W_A+\tau)]}{\partial r} \\ &= \frac{\partial \phi}{\partial r}\left[\left(1 - \frac{\bar{\lambda}}{\mu}\right)(\phi)^{-1/2} - \frac{\beta}{w_0}\frac{1}{W_A+\tau}\frac{1}{\bar{\lambda}}f(r)\right] \end{aligned} \tag{39}$$

where the second equality follows from (36). As a result, if $g(r) < 0$ (equivalently, $f(r) < 0$), then $g'(r) < 0$, which implies that if $g(\hat{r}) < 0$ (equivalently, $f(\hat{r}) < 0$), then $g(r) < 0$ (equivalently, $f(r) < 0$) for all $r \geq \hat{r}$. Hence, in Scenario 2, $f(r)$ has at most one zero. The principal's profit has three possibilities: (1) decreases in r, (2) first decreases then increases in r, (3) increases in r.

Scenario 3: Driver accepts all the rides. Hence,

$$\frac{v_A}{W_A + \tau} = \frac{bv_G + (1-b)v_B}{\frac{1}{\mu-\lambda} + \tau}.$$

As a result, $\dfrac{v_A}{W_A + \tau}$ does not change in r.

Therefore, if $\lambda(\beta, q, r) = \bar{\lambda}$, then the principal's profit first decreases in r, then increases in r. □

Proof of Lemma 1, Part 2: Here, we continue the proof of Lemma 1 by showing that given any β, it is without loss of optimality to assume $r = 0$. That is, the platform never sends a bad signal if it is a good ride. Since $\lambda(\beta, q, r)$ decreases in r, then give β, q it is possible to have the following three scenarios:

1. $\lambda(\beta, q, q) = \bar{\lambda}$: We have $\lambda(\beta, q, r) = \bar{\lambda}$ for any $r \in [0, q]$. Lemma 7 shows that the principal's profit first decreases in r, then increases in r. Hence, r^* equals to either 0 or q. If $r^* = q$, it is equivalent to set $q = r = 0$ (no information).

2. $\lambda(\beta, q, 0) < \bar{\lambda}$: We have $\lambda(\beta, q, r) < \bar{\lambda}$ for any $r \in [0, q]$, and the principal's profit is $\dfrac{1-\beta}{\beta} w_0 \lambda(\beta, q, r)$. Hence, $r^* = 0$.

3. $\lambda(\beta, q, q) < \bar{\lambda}$ and $\lambda(\beta, q, 0) = \bar{\lambda}$: We can define $\check{r} = \sup\{r \in (0, q) : \lambda(\beta, q, r) = \bar{\lambda}\}$ and at $\check{r}$, $\lambda(\beta, q, \check{r}) = \bar{\lambda}$ and $U(\bar{\lambda}, \beta, q, \check{r}) = 0$. Following Lemma 7 and the property of $\lambda(\beta, q, r)$, we have r^* equals to either r or $\check{r}$. If $r^* = \check{r}$, then the optimal profit is $\dfrac{1-\beta}{\beta} w_0 \bar{\lambda}$. Since $\lambda(\beta, 0, 0) = \lambda(\beta, q, q) < \bar{\lambda}$ and $\lambda(\beta, 1, 0) = \lambda(\beta, q, 0) = \bar{\lambda}$, there exists $\check{q}$ such that $\lambda(\beta, \check{q}, 0) = \bar{\lambda}$ and $U(\bar{\lambda}, \beta, \check{q}, 0) = 0$. As a result, the principal's profit under $q = \tilde{q}$ and $r = 0$ achieves $\dfrac{1-\beta}{\beta} w_0 \bar{\lambda}$.

In all of the above scenarios, the optimal profit can be achieved by setting $r = 0$. □

Proof of Lemma 2

The derivations are straightforward; hence, the detailed proofs are omitted here. □

Proof of Proposition 1

We prove the following statement:

1. If $\lambda \le \tilde{\lambda}_1(\beta, q)$, then the worker only accepts the good signals. Moreover, $\mu_A = \mu_{\mathcal{G}}$, $x^* = 1$, and $y^* = 0$.

2. If $\tilde{\lambda}_1(\beta, q) < \lambda < \tilde{\lambda}_2(\beta)$ and $\phi(\beta) \ge 1$, then the worker accepts all good signals and part of the bad signals. Moreover, $\mu_A = \lambda(1 + \dfrac{1}{\sqrt{\phi(\beta)} - 1})$, $x^* = 1$, and $y^* = \dfrac{\mu_A - \mu(b + (1-q)(1-b))}{\mu(1-b)q}$.

3. If $\lambda \ge \tilde{\lambda}_2(\beta)$, then the worker accepts all signals. That is, $\mu_A = \mu$, $x^* = 1$, and $y^* = 1$.

where

$$\tilde{\lambda}_1(\beta, q) := \mu(b + (1-b)(1-q)) \left(1 - 1/\sqrt{\phi(\beta)}\right), \tag{40}$$

$$\tilde{\lambda}_2(\beta) := \mu \left(1 - 1/\sqrt{\phi(\beta)}\right), \tag{41}$$

and

$$\phi(\beta) := \frac{\beta(v_{\mathcal{G}} - v_{\mathcal{B}})\mu(b + (1-b)(1-q))}{w_0} = \frac{\beta(v_G - v_B)\mu b}{w_0}.$$

It can be verified that $\varphi(\beta)$ in Proposition 1 is defined as

$$\varphi(\beta) = 1 - 1/\sqrt{\phi(\beta)}$$

The rest of the proof follows through by replacing the terms involving $\phi(\beta)$ with $\varphi(\beta)$.

Optimization Problem (6) reformulation

We can further apply a change of variables to transform the problem by defining the following variables:

$$\hat{x} = \frac{x\mu_{\mathcal{G}}}{\mu_A} \tag{42}$$

and

$$W = \frac{1}{\mu_A - \lambda} \tag{43}$$

where $\hat{x}$ represents the proportion of requests among all acceptable requests that are good requests. Thus, $(1-\hat{x})$ represents the proportion of acceptable requests that are bad requests. Variable W is just the waiting time.

By the change of variable, we transform the objective (6) into one where the driver chooses the total rate and the composition of the acceptable requests, subject to the arrival rate of each type of request. Formally, the reformulated problem is given by:

$$\max_{\hat{x},W} \ \beta(\hat{x}v_{\mathcal{G}} + (1-\hat{x})v_{\mathcal{B}}) - w_0(W+\tau) \tag{44}$$

s.t.

$$(\lambda + \frac{1}{W})\hat{x} \leq \mu_{\mathcal{G}} \tag{45}$$

$$\hat{x} \leq 1 \tag{46}$$

$$W \geq \frac{1}{\mu - \lambda} \tag{47}$$

Note that the term $(\lambda + 1/W)$ is just the average rate of acceptable requests, μ_A. Thus, Eq. (45) simply represents that the driver cannot accept more requests with signal $\mathcal{G}$ than their arrival rate. An analogous condition can be derived for requests with signal $\mathcal{B}$, which does not affect the results and is therefore omitted for brevity.

We can then multiply both sides by W for Eq. (45) - Eq. (47), which gives the constraints:

$$(\lambda W + 1)\hat{x} \leq \mu_{\mathcal{G}} W \tag{48}$$

$$\hat{x} \leq 1 \tag{49}$$

$$W \geq \frac{1}{\mu - \lambda} \tag{50}$$

Optimality conditions

The Lagrange function for the above problem is given by

$$L(\hat{x}, \hat{y}, W, \beta_1, \beta_2, \beta_3, \beta_4) = w_0(W+\tau) - \hat{x}\beta v_{\mathcal{G}} - (1-\hat{x})\beta v_{\mathcal{B}} + \alpha_1((\lambda W + 1)\hat{x} - \mu_{\mathcal{G}} W) + \alpha_2(\hat{x} - 1) + \alpha_3\left(\frac{1}{\mu - \lambda} - W\right) \tag{51}$$

Then by applying the Karush–Kuhn–Tucker conditions, we have the following necessary conditions for the optimal solution:

$$\frac{\partial L}{\partial \hat{x}} = -\beta v_{\mathcal{G}} + \beta v_{\mathcal{B}} + \alpha_1(\lambda W + 1) + \alpha_2 = 0 \tag{52}$$

$$\frac{\partial L}{\partial W} = w_0 + \alpha_1(\lambda\hat{x} - \mu_{\mathcal{G}}) - \alpha_3 = 0 \tag{53}$$

The solution also has to satisfy the complementarity conditions

$$\alpha_1 \ ((\lambda W + 1)\hat{x} - \mu_{\mathcal{G}} W) = 0 \tag{54}$$

$$\alpha_2 \ (\hat{x} + \hat{y} - 1) = 0 \tag{55}$$

$$\alpha_3 \left(\frac{1}{\mu - \lambda} - W\right) = 0 \tag{56}$$

We verify the solutions in Proposition 1 in three scenarios.

1. Under scenario 1 in Proposition 1, we can verify that

$$\hat{x}^* = 1, W^* = \frac{1}{\mu_{\mathcal{G}} - \lambda},$$

with

$$\alpha_1 = \frac{w_0}{\mu_{\mathcal{G}} - \lambda}, \alpha_2 = \beta(v_{\mathcal{G}} - v_{\mathcal{B}}) - \frac{w_0 \mu_{\mathcal{G}}}{(\mu_{\mathcal{G}} - \lambda)^2} \geq 0, \alpha_3 = 0,$$

satisfy all the above optimality conditions. Furthermore, $\mu_A = \mu_{\mathcal{G}}$, $x^* = 1$, $y^* = 0$.

2. Under scenario 2 in Proposition 1, we can verify that

$$\hat{x}^* = \frac{\mu_{\mathcal{G}}}{\lambda\left(1 + 1/(\sqrt{\phi(\beta)} - 1)\right)}, W^* = \frac{1}{\lambda}(\sqrt{\phi(\beta)} - 1),$$

with

$$\alpha_1 = \frac{w_0}{\sqrt{\phi(\beta)} - 1}, \alpha_2 = 0, \alpha_3 = 0.$$

satisfy all the above optimality conditions. Furthermore, $\mu_A = \lambda(1 + \frac{1}{\sqrt{\phi(\beta)} - 1})$, $x^* = 1$, $y^* = \frac{\mu_A - \mu(b + (1-q)(1-b))}{\mu(1-b)q}$.

3. Under scenario 2 in Proposition 1, we can verify that

$$\hat{x}^* = \frac{\mu_{\mathcal{G}}}{\mu}, W^* = \frac{1}{\mu - \lambda},$$

with

$$\alpha_1 = \frac{\beta(v_{\mathcal{G}} - v_{\mathcal{B}})(\mu - \lambda)}{\mu}, \alpha_2 = 0, \alpha_3 = w_0 - \beta(v_{\mathcal{G}} - v_{\mathcal{B}})\mu_{\mathcal{G}} \frac{(\mu - \lambda)^2}{\mu^2},$$

satisfy all the above optimality conditions. Furthermore, $\mu_A = \mu$, $x^* = 1$, and $y^* = 1$. □

Proof of Proposition 2, Part (i)

We first prove that $\lambda(\beta, q)$ is increasing in q. Recall that by the definition of $\lambda(\beta, q)$ in Eq. (7), $\lambda(\beta, q)$ is the minimum of the arrival rate λ^* such that $U(\lambda^*, \beta, q) = 0$ and the size of the worker pool $\bar{\lambda}$. Since our goal is to prove weak monotonicity, it is equivalent to prove that λ^* is weakly increasing in q, where $U(\lambda^*, \beta, q) = 0$.

We prove the above statement in two steps, which we summarize as two lemmas about the worker's utility $U(\lambda, \beta, q)$:

Lemma 8. *Fixing λ and β, the utility $U(\lambda, \beta, q)$ is weakly increasing in q. That is,*

$$U(\lambda, \beta, q) \leq U(\lambda, \beta, q'), \text{ if } q' > q \tag{57}$$

Lemma 9. *Fixing q and β, the utility $U(\lambda, \beta, q)$ is strictly decreasing in λ. That is,*

$$U(\lambda, \beta, q) > U(\lambda', \beta, q), \text{ if } \lambda < \lambda' \tag{58}$$

The proof for Lemma 8 and Lemma 9 are detailed at the end of the proof.

Combining the two lemmas above, we are able to show that λ^*, which is defined as the largest λ such that $U(\lambda^*, \beta, q) = 0$, is weakly increasing in q for any given β. To see why, let λ^*_q denote the arrival rate under information policy q, such that $U(\lambda^*_q, \beta, q) = 0$; let $\lambda^*_{q'}$ denote the arrival rate under information policy q', such that $U(\lambda^*_{q'}, \beta, q') = 0$. Assume that $q > q'$.

Then by Lemma 8,

$$U(\lambda^*_{q'}, \beta, q') = 0 \leq U(\lambda^*_{q'}, \beta, q) \tag{59}$$

In other words, the utility is greater than or equal to zero under information policy q, commission rate β, and the arrival rate

$\lambda^*_{q'}$. But by the definition of λ^*_q, we also know that

$$U(\lambda^*_q, \beta, q) = 0 \tag{60}$$

which implies

$$U(\lambda^*_q, \beta, q) \leq U(\lambda^*_{q'}, \beta, q) \tag{61}$$

Then by Lemma 9, the following must also be true:

$$\lambda^*_q \geq \lambda^*_{q'} \tag{62}$$

Proof of Lemma 8 We show that for any information policy $q < 1$, an information policy $q' > q$ can always achieve at least the same worker utility. In particular, this proof relies on (1) a transformation of the worker utility maximization problem introduced in Section 3; and (2) a conclusion implied by the optimal worker strategy from Proposition 1 that all requests with the good signal will always be accepted by workers under the optimal strategy (which can be seen from $x^* = 1$ in all three cases from Proposition 1). We start by introducing the transformation of the problem.

Worker problem transformation. We first define the following term, $\hat{x}$, which represents the proportion of good requests among all requests that are acceptable to the workers. Note that "good" here means the request is associated with a good signal, which is consistent with our definition in Section 3. More specifically, $\hat{x}$ can be written as the following:

$$\hat{x} = \frac{x \cdot \mu(b + (1-b)(1-q))}{\mu_A} \tag{63}$$

where the numerator represents the arrival rate of the good requests and μ_A represents the arrival rate of all acceptable requests. Thus, we can rewrite the worker's utility maximization problem Eq. (6) as the following:

$$\max_{\hat{x}, \mu_A} U = \beta(\hat{x} v_{\mathcal{G}} + (1-\hat{x}) v_B) - w_0(\frac{1}{\mu_A - \lambda} + \tau) \tag{64}$$

where $v_{\mathcal{G}}$ represents the value of the good requests, as defined by Eq. (2). For the ease of exposition, we repeat the definition here and parameterize it with q:

$$v_{\mathcal{G}}(q) = \frac{b v_G + (1-q)(1-b) v_B}{b + (1-q)(1-b)} \tag{65}$$

Furthermore, according to Eq. (1), the arrival rate of requests with the good signal is also a function of q, which we repeat here:

$$\mu_{\mathcal{G}}(q) = \mu(b + (1-b)(1-q)) \tag{66}$$

Now we are ready to formally define the statement to prove:

Statement. Given λ and β, for any information policy $q < 1$, its corresponding optimal worker utility $U(\lambda, \beta, q)$ can always be achieved under an information policy $q' > q$.

Proof. Consider exogenous λ and β. Denote the optimal worker strategy under q to be $\hat{x}^*$ and μ^*_A. Then by Proposition 1, it must be true that all $\mu_{\mathcal{G}}(q)$ good signals are accepted, and $(\mu^*_A - \mu_{\mathcal{G}}(q))$ bad signals are accepted, where $\mu^*_A - \mu_{\mathcal{G}}(q) \geq 0$; as a result, it must also be true that

$$\hat{x}^* = \frac{\mu_{\mathcal{G}}(q)}{\mu^*_A} \tag{67}$$

Thus, the optimal utility under information policy q is given by

$$U^*(\lambda, \beta, q) = \beta(\hat{x}^* \cdot v_{\mathcal{G}}(q) + (1-\hat{x}^*) \cdot v_B) - w_0(\frac{1}{\mu^*_A - \lambda} + \tau) \tag{68}$$

Now consider an information policy $q' > q$. It is easy to observe from Eq. (65) and Eq. (66) that $v_{\mathcal{G}}(q)$ is increasing in q and $\mu_{\mathcal{G}}(q)$ is decreasing in q (i.e. with more information, the quality of the good signal is better, but there are fewer good signals.) Thus, $v_{\mathcal{G}}(q') > v_{\mathcal{G}}(q)$ and $\mu_{\mathcal{G}}(q') < \mu_{\mathcal{G}}(q)$.

Let the worker strategy be that the rate of all acceptable requests remains to be μ_A^*. That is, the worker accepts $\mu_{\mathcal{G}}(q')$ good signals and $(\mu_A^* - \mu_{\mathcal{G}}(q'))$ bad signals. Note that such a strategy is always feasible for $q' > q$, because of the monotonicity of $\mu_{\mathcal{G}}(q)$ mentioned above; that is,

$$\mu_A^* - \mu_{\mathcal{G}}(q') > \mu_A^* - \mu_{\mathcal{G}}(q) \geq 0$$

Thus, the worker utility under strategy (x', μ_A^*) is given by

$$U = \beta(x' \cdot v_{\mathcal{G}}(q') + (1 - x') \cdot v_B) - w_0(\frac{1}{\mu_A^* - \lambda} + \tau) \tag{69}$$

where x' represents the proportion of good signals across all acceptable requests, under information policy q' and the worker strategy described above. More specifically, x' satisfies:

$$x' = \frac{\mu_{\mathcal{G}}(q')}{\mu_A^*} \tag{70}$$

Next, we compute the difference between U and $U^*(\lambda, \beta, q)$ and show that it is non-negative.

$$\begin{aligned}
&U - U^*(\lambda, \beta, q)\\
=&\left(\beta(\hat{x}^* \cdot v_{\mathcal{G}}(q) + (1 - \hat{x}^*) \cdot v_B) - w_0(\frac{1}{\mu_A^* - \lambda} + \tau)\right) - \left(\beta(x' \cdot v_{\mathcal{G}}(q') + (1 - x') \cdot v_B) - w_0(\frac{1}{\mu_A^* - \lambda} + \tau)\right)\\
=&\beta\left(\hat{x}^* \cdot v_{\mathcal{G}}(q) + (1 - \hat{x}^*) \cdot v_B - (x' \cdot v_{\mathcal{G}}(q') + (1 - x') \cdot v_B)\right)
\end{aligned}$$

Note that we can compute the first part within the prentices in the following way below by plugging in Eq. (67), Eq. (65), and Eq. (66):

$$\begin{aligned}
&\hat{x}^* \cdot v_{\mathcal{G}}(q) + (1 - \hat{x}^*) \cdot v_B\\
=&\frac{\mu_{\mathcal{G}}(q)}{\mu_A^*} \cdot v_{\mathcal{G}}(q) + (1 - \frac{\mu_{\mathcal{G}}(q)}{\mu_A^*})v_B\\
=&\frac{\mu(b + (1-b)(1-q))}{\mu_A^*} \cdot \frac{bv_G + (1-q)(1-b)v_B}{b + (1-q)(1-b)} + (1 - \frac{\mu(b + (1-b)(1-q))}{\mu_A^*})v_B\\
=&\frac{\mu}{\mu_A^*}\left((b + (1-b)(1-q)) \cdot \frac{bv_G + (1-q)(1-b)v_B}{b + (1-q)(1-b)} + (\frac{\mu_A^*}{\mu} - (b + (1-b)(1-q)))v_B\right)\\
=&\frac{\mu}{\mu_A^*}\left(bv_G + (1-q)(1-b)v_B + \frac{\mu_A^*}{\mu}v_B - (b + (1-b)(1-q))v_B\right)\\
=&\frac{\mu}{\mu_A^*}(bv_G + \frac{\mu_A^*}{\mu}v_B - bv_B) = \frac{\mu}{\mu_A^*}b(v_G - v_B) + v_B
\end{aligned}$$

In other words, all terms containing q cancel out and the function $(\hat{x}^* \cdot v_{\mathcal{G}}(q) + (1 - \hat{x}^*) \cdot v_B)$ does not change in q. Since the term $(x' \cdot v_{\mathcal{G}}(q') + (1 - x') \cdot v_B)$ is defined in the same fashion except under a different information policy q', one can verify that the calculation leads to the same value that does not contain q'. Thus, we have

$$U = U^*(\lambda, \beta, q)$$

Given that the worker strategy (x', μ_A^*) is not necessarily an optimal strategy under q' (μ_A^* is not an optimal decision), the optimal worker utility under q' must satisfy

$$U^*(\lambda, \beta, q') \geq U = U^*(\lambda, \beta, q)$$

This concludes the proof. □

Proof of Lemma 9: In this proof, we show that the worker's utility $U(\lambda, \beta, q)$ is weakly increasing in λ. We prove this by the same transformation used in the proof of Lemma 9. Thus, we do not repeat the transformation here. One can observe from Eq. (64) that the main tradeoff is between the average value term $\hat{x}v_{\mathcal{G}} + (1 - \hat{x})v_B$ and the waiting time term $\frac{1}{\mu_A - \lambda}$. All else being equal, accepting more good rides improve both the average value and the waiting time; thus, a worker should always accept all good rides. However, when it comes to accepting bad rides, the tradeoff appears; accepting more bad rides reduces the waiting time, but will reduce the average value. Thus, we can derive the following constraint for $\hat{x}$:

$$b + (1-b)(1-q) \leq \hat{x} \leq 1 \tag{71}$$

In other words, it is never optimal to choose $\hat{x}$ below $b + (1-b)(1-q)$, otherwise it means not all good rides are accepted. In addition,

$$\mu_A \hat{x} = \mu(b + (1-b)(1-q)) \tag{72}$$

In other words, the transformed problem involves the worker choosing the arrival rate of the acceptable requests μ_A and the composition of the acceptable requests which is controlled by $\hat{x}$. Nonetheless, none of the constraints are related to the arrival rate λ. Hence, we can directly apply the envelope theorem to compute the partial derivative over λ:

Denote the optimal utility from the above optimization problem as $U^*(\hat{x}^*, \mu_A^*)$. Note that $U^*(\hat{x}^*, \mu_A^*)$ is mathematically equivalent to $U(\lambda, \beta, q)$, but just parameterized by the decision variables in Eq. (64) rather than the exogenous parameters λ, β, and q. Then we can apply the envelope theorem:

$$\frac{\partial U^*(\hat{x}^*, \mu_A^*)}{\partial \lambda} = -w_0 \frac{1}{(\mu_A - \lambda)^2} < 0 \tag{73}$$

This concludes our proof. □

Proof of Proposition 2, Part (ii)

First, we characterize the conditions for each segment in Fig. 3b. Define $\sigma = \sqrt{\mu(v_G - v_B)b/w_0}$ and $\theta = \sqrt{\mu_{\mathcal{G}} v_{\mathcal{G}}/w_0}$. One can compute by the definition of $\mu_{\mathcal{G}}$ and $v_{\mathcal{G}}$ that

$$\mu_{\mathcal{G}} v_{\mathcal{G}} = \mu(b v_G + (1-q)(1-b) v_B) \tag{74}$$

Therefore, $\mu_{\mathcal{G}} v_{\mathcal{G}}$ is a function of q and is strictly decreasing in q. Thus, we add a subscript q for θ to emphasize the relationship. Following this notation, $\theta_0 = \sqrt{\mu(b v_G + (1-b) v_B)/w_0} = \sqrt{\mu \bar{v}/w_0}$, and $\theta_q = \sqrt{\mu(b v_G + (1-q)(1-b) v_B)/w_0} < \theta_0$.

- Region 1: The region where the workers accept only good requests, and the equilibrium arrival rate is below $\bar{\lambda}$:

$$\frac{w_0}{v_{\mathcal{G}}} \left(\frac{1}{\mu_{\mathcal{G}}} + \tau \right) \leq \beta < \frac{1}{v_{\mathcal{G}}} (w_0 \tau + \frac{w_0}{(\mu_{\mathcal{G}} - \bar{\lambda})^+}), \ \beta < \frac{(\sigma + \sqrt{\sigma^2 + 4\theta_q^2 \mu_{\mathcal{G}} \tau})^2}{4\theta_q^4} \tag{75}$$

  Note that the first condition always holds if $\mu_{\mathcal{G}} \leq \bar{\lambda}$.

- Region 3(a): The region where the workers accept all requests under information policy q, and the equilibrium arrival rate is below $\bar{\lambda}$.

$$\beta \geq \frac{w_0}{\bar{v}} \left(\frac{1}{\mu} + \tau \right), \frac{(\sigma + \sqrt{\sigma^2 + 4\theta_0^2 \mu \tau})^2}{4\theta_0^4} \leq \beta < \frac{1}{\bar{v}} (w_0 \tau + \frac{w_0}{(\mu - \bar{\lambda})^+}) \tag{76}$$

- Region 3(b): The region where the workers accept all requests under information policy q, and the equilibrium arrival rate is at $\bar{\lambda}$:

$$\frac{1}{\bar{v}} (w_0 \tau + \frac{w_0}{(\mu - \bar{\lambda})^+}) \leq \beta \leq \frac{1}{\sigma^2((1 - \bar{\lambda}/\mu)^+)^2} \tag{77}$$

- Region 5: The region where the workers accept only good requests, and the equilibrium arrival rate is at $\bar{\lambda}$:

$$\beta \geq \frac{1}{v_{\mathcal{G}}} (w_0 \tau + \frac{w_0}{(\mu_{\mathcal{G}} - \bar{\lambda})^+}), \ \beta > \frac{1}{\sigma^2((1 - \bar{\lambda}/\mu_{\mathcal{G}})^+)^2} \tag{78}$$

  Clearly, this case can only happen if $\mu_{\mathcal{G}} > \bar{\lambda}$.

  Hence, if all the above regions exist, then as β increases, moving from region 1 to region 3(a), workers cherry-pick less with $\lambda(\beta, q) < \bar{\lambda}$. Furthermore, moving from region 3(b) to region 5, workers cherry-pick more with $\lambda(\beta, q) = \bar{\lambda}$. □

Preparation to the proof of Theorem 1

Proof of Proposition 4

We only need to verify that if $\pi(\beta_j^*(q), q) > 0$, then under $\beta_j^*(q)$, the worker utility $U(\lambda(\beta_j^*(q), q), \beta_j^*(q), q) = 0$.

If $\lambda(1, q) < \bar{\lambda}$, then following Proposition 2, we have $\lambda(\beta, q) < \bar{\lambda}$ for any β. Hence, by definition of $\lambda(\beta, q)$, we have $U(\lambda(\beta, q), \beta, q) = 0$ for any β, which implies the result.

If $\lambda(1, q) = \bar{\lambda}$, then we denote $\bar{\beta}(q) := \min\{\beta | \lambda(\bar{\beta}(q), q) = \bar{\lambda}\}$. Hence, for $\beta \leq \bar{\beta}(q)$, we have $U(\lambda(\beta, q), \beta, q) = 0$. Therefore, the desired results follow from if $\beta > \bar{\beta}(q)$, then the profit function $\pi(\beta, q)$ strictly decreases in q. If $\beta \geq \bar{\beta}(q)$, then the profit function is

$$\pi(\beta, q) = \bar{\lambda}(1 - \beta)\frac{v_A}{W_A + \tau}$$

We show the property of $\pi(\beta, q)$ in three scenarios.

1. If $\bar{\lambda} \leq \tilde{\lambda}_1(\beta, q)$, then

$$\frac{v_A}{W_A + \tau} = \frac{v_{\mathcal{G}}}{1/(\mu b_q - \bar{\lambda}) + \tau}.$$

   which is not a function of β. Hence, $\pi(\beta, q)$ decrease in β.

2. If $\bar{\lambda} \in (\tilde{\lambda}_1(\beta, q), \tilde{\lambda}_2(\beta))$,

$$\frac{v_A}{W_A + \tau} = \frac{1}{W_A + \tau}\left[\frac{\mu b(v_G - v_B)}{\mu_A} + v_B\right] := \mathcal{F}(\beta)$$

$$\mathcal{F}'(\beta) = -\frac{1}{(W_A + \tau)^2}\left[\frac{\mu b(v_G - v_B)}{\mu_A} + v_B\right]\frac{1}{2\bar{\lambda}}\hat{A}\phi^{-1/2} + \frac{1}{W_A + \tau}\mu b(v_G - v_B)\frac{1}{2\bar{\lambda}}\phi^{-3/2}\hat{A}$$

   which has the same sign with

$$\begin{aligned}&\frac{1}{(W_A + \tau)}\left[\frac{w_0}{\beta} - \frac{1}{(W_A + \tau)}\left(\frac{\mu b(v_G - v_B)}{\mu_A} + v_B\right)\right]\\ =&\frac{1}{(W_A + \tau)}\left[\frac{w_0}{\beta} - \frac{v_A}{(W_A + \tau)}\right] < 0\end{aligned}$$

   where $\hat{A} = (v_G - v_B)\mu b/w_0$, and the inequality follows from $U = \beta v_A - w_0(W_A + \tau) > 0$ (implied by $\beta > \beta(q)$).

3. If $\bar{\lambda} \geq \tilde{\lambda}_2(\beta)$, then

$$\frac{v_A}{W_A + \tau} = \frac{bv_G + (1 - b)v_B}{1/(\mu - \bar{\lambda}) + \tau}.$$

   which is not a function of β. Hence, $\pi(\beta, q)$ decrease in β. □

Proof of Theorem 1

We prove Theorem 1 by showing that in each individual scenario j, the platform's profit π_j is maximized under full information. Thus, in the proof below, we only consider a single demand scenario and drop the subscript j.

The core of our proof relies on a transformation of the profit function π, introduced by Eq. (9). By Eq. (9),

$$\pi(\beta, q) = \frac{1}{\tau + W(\lambda(\beta, q); \mu_A)}\lambda(\beta, q)(1 - \beta)v_A(\beta, q) \tag{79}$$

The profit $\pi(\beta, q)$ can be rewritten into a simpler form by leveraging Proposition 4 that we introduce below:

Applying Proposition 4, by the definition of the worker utility U, the following must be true when the commission rate is at

$\beta^* = \beta_j^*(q)$:

$$U(\lambda(\beta^*, q), \beta^*, q) = 0 \Leftrightarrow \beta^* v_A(\beta^*, q) - w_0(W(\lambda(\beta^*, q); \mu_A); \mu_A) + \tau) = 0 \tag{80}$$

which further implies that

$$\beta^* v_A(\beta^*, q) = w_0(W(\lambda(\beta^*, q); \mu_A) + \tau) \tag{81}$$

Applying Eq. (81) to Eq. (79), we have the following alternative formula for the profit at the optimal commission rate β^*:

$$\pi(\beta^*, q) = \frac{1}{\beta^* v_A(\beta^*, q)/w_0} \lambda(\beta^*, q)(1 - \beta^*) v_A(\beta^*, q) \tag{82}$$

$$= \frac{1}{\beta^*/w_0} \lambda(\beta^*, q)(1 - \beta^*) \tag{83}$$

$$= w_0 \lambda(\beta^*, q) \frac{1 - \beta^*}{\beta^*} \tag{84}$$

Therefore, identifying the profit maximizing information policy q (with its corresponding optimal commission rate β^*) is equivalent to comparing the product of $\lambda(\beta^*, q)$ and $(1 - \beta^*)/\beta^*$ for all information policy $0 \leq q \leq 1$.

Next, we prove that full information ($q = 1$) leads to the highest profit. In particular, we denote the optimal commission rate under full information as $\beta_j^*(1)$ and the optimal commission rate under all other information policies as $\beta_j^*(q)$ with $q < 1$. We prove the statement by contradiction:

Suppose not. Then there exists an information policy $q < 1$ that leads to a strictly higher profit. That is,

$$\lambda(\beta_j^*(q), q) \frac{1 - \beta_j^*(q)}{\beta_j^*(q)} > \lambda(\beta_j^*(1), 1) \frac{1 - \beta_j^*(1)}{\beta_j^*(1)} \tag{85}$$

Moreover, since $\beta_j^*(1)$ is the profit-maximizing commission rate under full information, it must also be true that

$$\lambda(\beta_j^*(1), 1) \frac{1 - \beta_j^*(1)}{\beta_j^*(1)} \geq \lambda(\beta_j^*(q), 1) \frac{1 - \beta_j^*(q)}{\beta_j^*(q)} \tag{86}$$

Combining the two inequalities above, it must be true that

$$\lambda(\beta_j^*(q), q) \frac{1 - \beta_j^*(q)}{\beta_j^*(q)} > \lambda(\beta_j^*(q), 1) \frac{1 - \beta_j^*(q)}{\beta_j^*(q)} \tag{87}$$

which implies that

$$\lambda(\beta_j^*(q), q) > \lambda(\beta_j^*(q), 1) \tag{88}$$

But according to Proposition 2, this cannot be true. Contradiction. This concludes our proof. □

Preparation to the proof of Proposition 5

The following Proposition 11 provides the derivation of the optimal commission rate under no information and single demand scenario.

Proposition 11. *Under a demand scenario j with $\mu_j = \mu$ amd no information policy, the optimal commission rate is given by:*

$$\beta_j^*(0) := \min\left\{\check{\beta}_0(\mu), \bar{\beta}^0(\mu)\right\}, \tag{89}$$

where

$$\bar{\beta}^0(\mu) = \frac{1}{V}\left(\frac{1}{(\mu - \bar{\lambda})^+} + \tau\right), \tag{90}$$

and

$$\check{\beta}_0(\mu) := \frac{\mu \cdot V \cdot \tau + V + \sqrt{\mu \cdot V^2 \cdot \tau - \mu \cdot V \cdot \tau^2 + V^2 - V \cdot \tau}}{\mu \cdot V^2 + V}, \tag{91}$$

where $V = (bv_G + (1-b)v_B)/w_0$.

Proof of Proposition 11

Given any demand scenario μ_j, under no information, we derive the expression of $\pi_j(\beta, 0)$ in different scenarios of β. The platform's profit can be expressed as

$$\pi_j(\beta,0) = \begin{cases} 0 & \text{for } \beta \le \underline{\beta}_j^0, \\ \dfrac{w_0}{\beta}\lambda_j(\beta,0)(1-\beta), & \text{for } \beta \in \left(\underline{\beta}_j^0, \min\{\bar{\beta}_j^0, 1\}\right], \\ \dfrac{1}{\tau + 1/(\mu_j - \bar{\lambda})}\bar{\lambda}(1-\beta)(\beta v_G + (1-\beta)v_B), & \text{for } \beta \ge \min\{\bar{\beta}_j^0, 1\}, \end{cases} \tag{92}$$

where

$$\bar{\beta}_j^0 := \frac{1}{V}\left(\frac{1}{\mu_j - \bar{\lambda}} + \tau\right), \underline{\beta}_j^0 := \frac{1}{V}\left(\frac{1}{\mu_j} + \tau\right). \tag{93}$$

and

$$\lambda_j(\beta, 0) = \mu_j - \frac{1}{V\beta - \tau}, \quad \text{for} \quad \beta \in \left(\underline{\beta}_j^0, \min\{\bar{\beta}_j^0, 1\}\right], \tag{94}$$

since

1. If $\beta \in [0, \underline{\beta}_j^0]$ and $\lambda = 0$, then the driver's utility is

$$\beta(bv_G + (1-b)v_B) - w_0(1/\mu + \tau) \le \underline{\beta}(bv_G + (1-b)v_B) - w_0(1/\mu + \tau) = 0.$$

   Hence, $\lambda_j(\beta, 0) = \lambda_j^*(\beta, 0) = 0$ and $\pi_j(\beta, 0) = 0$.

2. If $\beta \in \left(\underline{\beta}_j^0, \min\{\bar{\beta}_j^0, 1\}\right]$, then

$$\lambda_j(\beta, 0) = \lambda^*(\beta, 0) = \mu_j - \frac{1}{V\beta - \tau} < \bar{\lambda},$$

   where the last inequality follows from $\beta < \bar{\beta}_j^0$.

$$\begin{aligned} \pi_j'(\beta,0) &= \frac{\tau}{(V\beta-\tau)^2 V\beta^2}\left(V\beta - V\beta^2 - \mu_j(V\beta-\tau)^2 + (V\beta - \tau)\right) \\ &= \frac{\tau}{(V\beta-\tau)^2 V\beta^2}\left(-(V+\mu_j V^2)\beta^2 + 2V(1+\tau\mu_j)\beta - (\tau + \mu_j\tau^2))\right). \end{aligned}$$

   First, it is straightforward to verify that $\check{\beta}_0(\mu_j) < 1$ and $\pi_j'(\check{\beta}_0(\mu_j), 0) = 0$. Furthermore, $\pi_j'(\beta, 0) < 0$ if $\beta < \check{\beta}_0(\mu_j)$, and $\pi_j'(\beta, 0) > 0$ if $\beta > \check{\beta}_0(\mu_j)$. Hence, if $\check{\beta}_0(\mu_j) \le \bar{\beta}_j^0$, then $\pi_j(\beta, 0)$ strictly increases in β for $\beta \in \left(\underline{\beta}_j^0, \check{\beta}_0(\mu_j)\right)$, and strictly decreases in β for $\beta \in \left(\check{\beta}_0(\mu_j), \min\{\bar{\beta}_j^0, 1\}\right)$. Otherwise, $\pi_j(\beta, 0)$ strictly increases in β for $\beta \in \left(\underline{\beta}_j^0, \min\{\bar{\beta}_j^0, 1\}\right)$.

3. If $\beta > \min\{\bar{\beta}_j^0, 1\}$, we have $\pi_j(\beta, 0)$ linearly decreases in β.

Therefore, we have shown that

$$\beta_j^*(0) \in (\underline{\beta}_j^0, \min\{\bar{\beta}_j^0, 1\}), \tag{95}$$

and $\pi_j(\beta, 0)$ strictly increases in β for $\beta < \beta_j^*(0)$, and strictly decreases in β for $\beta > \beta_j^*(0)$. Hence, $\beta_j^*(0) = \arg\max_\beta \pi_j(\beta, 0)$.
□

The following Lemma 10 describes the situation where driver's utility is greater than 0 under no information.

Lemma 10. *If* $\beta > \bar{\beta}_j^0$*, then* $\lambda_j(\beta, 0) = \bar{\lambda}$*, and driver's utility is greater than* 0*, i.e.,* $U(\lambda_j(\beta, 0), \beta, 0) > 0$.

Proof of Lemma 10

By definition of $\bar{\beta}_j^0$ in Eq. (93), we have $\lambda(\bar{\beta}_j^0, 0) = \bar{\lambda}$ and $U(\lambda(\beta, 0), \beta, 0) = 0$. Hence, the statement follows from Proposition 2 and Lemma 9. □

Proof of Proposition 5

First, Proposition 4 has shown that, under the upfront quote mechanism, the worker's expected utility is always zero. Hence, workers are always worse off under the upfront quote mechanism than under the flat rate mechanism.

Next, we show that under conditions Eq. (15) and Eq. (16), the worker's expected utility is strictly higher than 0. Following Eq. (10), Eq. (93), and Eq. (15), we have

$$1 > \underline{\beta}_1^0 \geq \bar{\beta}_2^0. \tag{96}$$

Hence, following Eq. (92), we have

$$\pi(\beta, 0) = f_1\pi_1(\beta, 0) + (1 - f_1)\pi_2(\beta, 0) \tag{97}$$

$$= \begin{cases} 0 & \text{for } \beta \leq \underline{\beta}_2^0, \\ (1 - f_1)\pi_2(\beta, 1), & \text{for } \beta \in \left(\underline{\beta}_2^0, \underline{\beta}_1^0\right], \\ f_1\pi_1(\beta, 1) + (1 - f_1)\pi_2(\beta, 1), & \text{for } \beta > \underline{\beta}_1^0. \end{cases} \tag{98}$$

Following Eq. (96) and Eq. (95), we have $\beta_2^*(0) = \arg\max_{\beta \in [0, \underline{\beta}_1^0]}$. Furthermore, Eq. (16) implies that $\pi(\beta_1^*(0), 0) > \pi(\beta_2^*(0), 0)$, which further implies that

$$\beta^* > \underline{\beta}_1^0 \geq \bar{\beta}_2^0.$$

where $\beta^* \in \arg\max_\beta \sum_j f_j\pi_j(\beta, 0)$. As a result, at $\beta = \beta^*$, Lemma 10 implies that the worker's utility under scenario 2 is higher than 0. Therefore, under conditions Eq. (15) and Eq. (16), the worker's expected utility is strictly higher than 0.

Proof of Lemma 3, Part (i) and (ii)

First, we let $\hat{\beta}_j^2$ and $\hat{\beta}_j^1$ solves

$$\tilde{\lambda}_2(\hat{\beta}_j^2, 1) = \bar{\lambda}, \tag{99}$$

$$\tilde{\lambda}_1(\hat{\beta}_j^1, 1) = \bar{\lambda} \tag{100}$$

We can verify that

$$\hat{\beta}_j^2 = \left(\frac{\mu_j}{\mu_j - \bar{\lambda}}\right)^2 \frac{w_0}{\mu_j b(v_G - v_B)}. \tag{101}$$

In the following, we characterize the driver's equilibrium participation level $\lambda(\beta, 1)$ under full information and the corresponding driver's acceptance strategy.

1. If $\beta \in [0, \underline{\beta}_j^0]$, where $\underline{\beta}_j^0$ is defined in (93), then

   $$\phi(\beta) \leq \frac{\mu_j b(v_G - v_B)}{w_0}\underline{\beta}_j^0 \leq 1$$

   where the second inequality follows from (17). As a result, following statement 3 of Proposition 1, we have $\tilde{\lambda}_2(\beta) \leq 0$. Hence, at $\lambda = 0$, the driver accepts all the rides (following statement 3 of the proof of Proposition 1), and the utility is

   $$\beta(bv_G + (1 - b)v_B) - w_0(1/\mu_j + \tau) \leq \underline{\beta}(bv_G + (1 - b)v_B) - w_0(1/\mu_j + \tau) = 0.$$

   Hence, $\lambda_j(\beta, 1) = 0$.

2. If $\beta \in [\underline{\beta}_j^0, \bar{\beta}_j^0]$, where $\bar{\beta}_j^0$ is defined in (93), let $\lambda = \lambda_3^*(\beta) \le \bar{\lambda}$, where

$$\lambda_3^*(\beta) = \mu_j - \frac{1}{\beta V - \tau} =: \mu_j - g_3(\beta),$$

then, if the driver accepts all the rides, the driver's utility is zero. To confirm that this is the driver's acceptance policy, we need to show that $\lambda_3^*(\beta) \ge \tilde{\lambda}_2(\beta, 1)$.

$$\tilde{\lambda}_2(\beta) = \mu_j \left(1 - \frac{1}{\sqrt{\phi(\beta)}}\right) = \mu_j - h_3(\beta)$$

$$\frac{h_3(\beta)}{g_3(\beta)} = \frac{\mu_j}{\sqrt{\phi}}(\beta V - \tau)$$

Clearly, $\frac{h_3(\beta)}{g_3(\beta)}$ increases in β, $\frac{h_3(\underline{\beta}_j^0)}{g_3(\underline{\beta}_j^0)} \ge 1$ implies that $\frac{h_3(\beta)}{g_3(\beta)} > 1$ and $\lambda_3^*(\beta) \ge \tilde{\lambda}_2(\beta)$ for $\beta \in [\underline{\beta}, \bar{\beta}]$. Hence, $\lambda_j(\beta, 1) = \lambda_3^*(\beta)$ and the driver accepts all the rides.

3. If $\beta \in [\bar{\beta}_j^0, \hat{\beta}_j^2]$, where $\hat{\beta}_j^2$ is defined in (99), then at $\lambda = \bar{\lambda}$, if the driver accepts all the rides, the driver's utility is greater than zero. To confirm that this is the driver's acceptance policy, we need to show that $\bar{\lambda} \ge \tilde{\lambda}_2(\beta, 1)$. $\tilde{\lambda}_2(\beta, 1)$ increases in β, hence, $\bar{\lambda} \ge \tilde{\lambda}_2(\beta, 1)$ follows from (99). Hence, $\lambda_j(\beta, 1) = \bar{\lambda}$, and the driver accepts all the rides.

4. If $\beta \in [\hat{\beta}_j^2, \hat{\beta}_j^1]$, where $\hat{\beta}_j^1$ is defined in (100), similar to case 3, we can verify that $\lambda_j(\beta, 1) = \bar{\lambda}$, and the driver accepts all the good rides and some bad rides, such that $W^* = 1/\bar{\lambda}(\sqrt{\phi(\beta)} - 1)$.

5. If $\beta \in [\hat{\beta}_j^1, 1]$, then we can verify that $\lambda_j(\beta, 1) = \bar{\lambda}$, and driver accepts only the good rides, i.e., $W^* = 1/(\mu b - \lambda)$.

Following the above analysis, for $\beta \in [0, \hat{\beta}_j^2]$, either $\lambda_j(\beta, 1) = 0$ or the driver accepts all the rides; hence, full information is the same as the no information. One immediate implication of the above result is that, following (92), we have

$$\pi_j(\beta, 1) = \pi_j(\beta, 0) = \begin{cases} 0 & \text{for } \beta \le \underline{\beta}_j^0, \\ \frac{w_0}{\beta}\lambda_j(\beta, 0)(1-\beta), & \text{for } \beta \in \left(\underline{\beta}_j^0, \min\{\bar{\beta}_j^0, 1\}\right], \\ \frac{1}{\tau + 1/(\mu_j - \bar{\lambda})}\bar{\lambda}(1-\beta)(\beta v_G + (1-\beta)v_B), & \text{for } \beta \in \left(\min\{\bar{\beta}_j^0, 1\}, \min\{\hat{\beta}_j^2, 1\}\right), \end{cases} \tag{102}$$

In the following, we only need to look at scenarios 4 and 5. In Scenario 4, for $\beta \in [\hat{\beta}_j^2, \hat{\beta}_j^1]$, we have in the no information

$$\pi_j(\beta, 0) = \frac{1}{W(\bar{\lambda}, \mu) + \tau}\bar{\lambda}(1-\beta)(b v_G + (1-b)v_B),$$

and

$$\pi_j(\beta, 1) = \frac{1}{W^* + \tau}\bar{\lambda}(1-\beta)\left[\frac{\mu_j b}{\bar{\lambda}}\left(1 - \frac{1}{\sqrt{\phi}}\right)v_G + \left(1 - \frac{\mu_j b}{\bar{\lambda}}\left(1 - \frac{1}{\sqrt{\phi}}\right)\right)v_B\right],$$

where $W^* = 1/\bar{\lambda}(\sqrt{\phi} - 1)$. Define

$$\begin{aligned} &\frac{\pi_j(\beta, 0)}{\bar{\lambda}(1-\beta)} - \frac{\pi_j(\beta, 1)}{\bar{\lambda}(1-\beta)} \\ =&\frac{b v_G + (1-b)v_B}{\tau + \frac{1}{\mu_j - \bar{\lambda}}} - \frac{1}{\tau + \frac{\sqrt{\phi}-1}{\bar{\lambda}}}\left[\frac{\mu_j b}{\bar{\lambda}}\left(1 - \frac{1}{\sqrt{\phi}}\right)v_G + \left(1 - \frac{\mu_j b}{\bar{\lambda}}\left(1 - \frac{1}{\sqrt{\phi}}\right)\right)v_B\right] \ge 0 \\ \Longleftrightarrow& \bar{v}\left(\tau + \frac{\sqrt{\phi}-1}{\bar{\lambda}}\right) \ge \left(\tau + \frac{1}{\mu_j - \bar{\lambda}}\right)\left[\frac{\mu_j b}{\bar{\lambda}}\left(1 - \frac{1}{\sqrt{\phi}}\right)(v_G - v_B) + v_B\right], \end{aligned}$$

if and only if

$$f(\beta) := \frac{\bar{v}}{\bar{\lambda}}\sqrt{\phi} + \left(\tau + \frac{1}{\mu_j - \bar{\lambda}}\right)\frac{\mu_j b(v_G - v_B)}{\bar{\lambda}}\frac{1}{\sqrt{\phi}} - \bar{v}\left(\tau - \frac{1}{\bar{\lambda}}\right) - \left(\tau + \frac{1}{\mu_j - \bar{\lambda}}\right)\left[\frac{\mu_j b}{\bar{\lambda}}(v_G - v_B) + v_B\right] \geq 0,$$

where $f(\hat{\beta}_j^2) = 0$. Furthermore, since $\frac{\partial \phi}{\partial \beta} > 0$, we have

$$f'(\beta) = \frac{\partial \phi}{\partial \beta}\left(\frac{\bar{v}}{\bar{\lambda}}\frac{1}{2}\phi^{-1/2} - \frac{1}{2}\left(\tau + \frac{1}{\mu_j - \bar{\lambda}}\right)\frac{\mu_j b(v_G - v_B)}{\bar{\lambda}}\phi^{-3/2}\right) > 0.$$

iff

$$\phi(\beta) > \left(\tau + \frac{1}{\mu_j - \bar{\lambda}}\right)\frac{\mu_j b(v_G - v_B)}{\bar{v}},$$

Since $\phi(\beta)$ increases in β, we only need to verify the above inequality when $\beta = \hat{\beta}_j^2$. Following (99), we have $\sqrt{\phi(\hat{\beta}_j^2)} = \frac{\mu_j}{\mu_j - \bar{\lambda}}$. Hence, we need to verify

$$\begin{aligned}
&\left(\frac{\mu_j}{\mu_j - \bar{\lambda}}\right)^2 \geq \left(\tau + \frac{1}{\mu_j - \bar{\lambda}}\right)\frac{\mu_j b(v_G - v_B)}{\bar{v}} \\
\Longleftrightarrow & \frac{\mu_j v_B + \bar{\lambda} b(v_G - v_B)}{(\mu_j - \bar{\lambda})^2} \geq b(v_G - v_B)\tau \\
\Longleftrightarrow & \mu_j v_B/v_G + \bar{\lambda} b(1 - v_B/v_G) \geq b(1 - v_B/v_G)\tau(\mu_j - \bar{\lambda})^2 \\
\Longleftrightarrow & [\mu_j - \bar{\lambda} b + b\tau(\mu_j - \bar{\lambda})^2]v_B/v_G \geq b\tau(\mu_j - \bar{\lambda})^2 - \bar{\lambda} b \\
\Longleftarrow & [\mu_j - \bar{\lambda} b + b\tau(\mu_j - \bar{\lambda})^2]\frac{\mu_j b\tau}{1 + \mu_j b\tau} \geq b\tau(\mu_j - \bar{\lambda})^2 - \bar{\lambda} b \\
\Longleftrightarrow & \bar{\lambda} \leq 2\mu_j + 1/\tau.
\end{aligned}$$

If the last equality does not hold, then $\bar{\lambda} \geq \mu$, and $\bar{\beta}_j^0 > 1$, that is, for any β, driver's utility is zero and $\lambda(\beta, 1) < \bar{\lambda}$, which will not belong to this case. Therefore, we have verified that $f(\beta) > 0$ for $\beta \in (\hat{\beta}_j^2, \hat{\beta}_j^1]$, which is equivalent to

$$\pi_j(\beta, 0) > \pi_j(\beta, 1). \tag{103}$$

for $\beta \in (\hat{\beta}_j^2, \hat{\beta}_j^1]$.

In Scenario 5, for $\beta \in [\hat{\beta}_j^1, 1]$, we have

$$\pi_j(\beta, 1) = \frac{1}{W(\bar{\lambda}, \mu_j b) + \tau}\bar{\lambda}(1 - \beta)v_G.$$

Then, for $\beta \in [\hat{\beta}_j^1, 1)$, we have

$$\frac{\pi_j(\beta, 0)}{\bar{\lambda}(1 - \beta)} - \frac{\pi_j(\beta, 1)}{\bar{\lambda}(1 - \beta)} = \frac{b v_G + (1 - b)v_B}{\tau + \frac{1}{\mu_j - \bar{\lambda}}} - \frac{v_G}{\tau + \frac{1}{\mu_j b - \bar{\lambda}}} > 0,$$

which follows from $f(\hat{\beta}_j^1) \geq 0$. Therefore, $f(\beta) > 0$ for $\beta \in (\hat{\beta}_j^1, 1)$, which is equivalent to

$$\pi_j(\beta, 0) > \pi_j(\beta, 1). \tag{104}$$

for $\beta \in (\hat{\beta}_j^1, 1)$. Clearly, we have shown that

$$\pi_j(\beta, 0) \geq \pi_j(\beta, 1),$$

for any β and $\pi_j(\beta, 0) > \pi_j(\beta, 1)$ for $\beta \in (\hat{\beta}_j^2, 1)$. Hence, following (102) and Proposition 11, we have $\pi_j(\beta_j^*(0), 1) = \pi_j(\beta_j^*(0), 0) > \pi_j(\beta, 0) \geq \pi_j(\beta, 0)$ for any $\beta \neq \beta_j^*(0)$, which implies that

$$\beta_j^*(0) = \arg\max_{\beta} \pi_j(\beta, 1), \beta_j^*(0) \in \left(\underline{\beta}_j^0, \min\{\bar{\beta}_j^0, 1\}\right) \tag{105}$$

under condition (17). Hence, we have shown part (i) and part (ii) by setting $\hat{\beta}_j := \hat{\beta}_j^2$. □

Proof of Lemma 3, Part (iii)

The desirable result follows from $\hat{\beta}_j = \hat{\beta}_j^2 > \bar{\beta}_j^0$ and Lemma 10. □

Corollary 2. *If $\mu_j < \bar{\lambda}$, then $\pi_j(\beta, 0) = \pi_j(\beta, 1)$ for any β.*

If $\mu_j < \bar{\lambda}$, we have $\lambda(\beta, 1) < \mu_j < \bar{\lambda}$, which implies that $\bar{\beta}_j^0 > 1$, hence following (102), we have $\pi_j(\beta, 0) = \pi_j(\beta, 1)$.

Proof of Proposition 7

First, following (101), and (93), condition Eq. (19), and Assumption 1, we have

$$\underline{\beta}_1^0 < 1, \hat{\beta}_2^2 < \underline{\beta}_1^0. \tag{106}$$

where $\underline{\beta}_j^0$ is defined in Eq. (93), and $\hat{\beta}_j^2$ is defined in Eq. (99). Hence, following Eq. (102), we have

$$\pi(\beta, 1) = f_1\pi_1(\beta, 1) + (1 - f_1)\pi_2(\beta, 1) \tag{107}$$

$$= \begin{cases} 0 & \text{for } \beta \leq \underline{\beta}_2^0, \\ (1 - f_1)\pi_2(\beta, 1), & \text{for } \beta \in \left(\underline{\beta}_2^0, \underline{\beta}_1^0\right], \\ f_1\pi_1(\beta, 1) + (1 - f_1)\pi_2(\beta, 1), & \text{for } \beta > \underline{\beta}_1^0. \end{cases} \tag{108}$$

Following (105), and $\hat{\beta}_2^2 < \underline{\beta}_1^0$ (from (106)), we have $\beta_2^*(1) = \beta_2^*(0) = \arg\max_{\beta \in [0, \underline{\beta}_1^0]} \pi(\beta, 1)$. Furthermore, condition Eq. (20) guarantees that $\pi(\beta_1^*(1), 1) > \pi(\beta_2^*(1), 1)$ and implies that $\beta_1^* > \underline{\beta}_1^0$, where $\beta_1^* \in \arg\max_\beta \pi(\beta, 1)$. Therefore,

$$\max_{\beta} \pi(\beta, 0) \geq \pi(\beta_1^*, 0) = f_1\pi_1(\beta_1^*, 0) + (1 - f_1)\pi_2(\beta_1^*, 0) > f_1\pi_1(\beta_1^*, 1) + (1 - f_1)\pi_2(\beta_1^*, 1) = \pi(\beta_1^*, 1)$$

where the second inequality follows from Lemma 3 and $\underline{\beta}_1^0 > \hat{\beta}_2$. □

Proof of Proposition 8

Following Eq. (10), Eq. (93), and Eq. (23), we have

$$1 > \underline{\beta}_1^0 \geq \bar{\beta}_2^0.$$

Hence, following Eq. (92), we have the platform's aggregate profit can be expressed as

$$\pi(\beta, 1) = f_1\pi_1(\beta, 1) + (1 - f_1)\pi_2(\beta, 1)$$
$$= \begin{cases} (1 - f_1)\pi_2(\beta, 1), & \text{for } \beta \leq \underline{\beta}_1^0, \\ f_1\pi_1(\beta, 1) + (1 - f_1)\pi_2(\beta, 1), & \text{for } \beta > \underline{\beta}_1^0, \end{cases}$$

Therefore, if the condition Eq. (24) also holds, then the platform's optimal commission rate is $\beta_2^*(1)$, which is the same as the optimal commission rate when the platform only faces demand scenario μ_2 and leads to a non-viable demand scenario μ_1. Therefore, following Proposition 4, the worker's utility is zero under full information.

Proof of Proposition 9

First, following (101), and (93), condition Eq. (19), and Assumption 1, we have

$$\underline{\beta}_1^0 < 1, \hat{\beta}_2^2 < \underline{\beta}_1^0.$$

where $\underline{\beta}_j^0$ is defined in Eq. (93), and $\hat{\beta}_j^2$ is defined in Eq. (99). Hence, following Eq. (102), we have

$$\begin{aligned}\pi(\beta,1) &= f_1\pi_1(\beta,1) + (1-f_1)\pi_2(\beta,1) \\ &= \begin{cases} 0 & \text{for } \beta \le \underline{\beta}_2^0, \\ (1-f_1)\pi_2(\beta,1), & \text{for } \beta \in \left(\underline{\beta}_2^0, \underline{\beta}_1^0\right], \\ f_1\pi_1(\beta,1) + (1-f_1)\pi_2(\beta,1), & \text{for } \beta > \underline{\beta}_1^0, \end{cases}\end{aligned}$$

which implies that $\beta_2^*(1) = \arg\max_{\beta \le \underline{\beta}_1^0} \pi(\beta,1)$ since $\beta_2^*(1)$ is the optimal commission rate if the platform only faces demand scenario μ_2.

As f_1 increases, the difference between the peak of the aggregate profit function left to $\underline{\beta}_1^0$ ($\max_{\beta \le \underline{\beta}_1^0} \pi(\beta,1)$) and the peak right to $\underline{\beta}_1^0$ ($\max_{\beta > \underline{\beta}_1^0} \pi(\beta,1)$) becomes smaller. Hence, there exists f_1^* such that if $f_1 = f_1^*$, then $\max_{\beta \le \underline{\beta}_1^0} \pi(\beta,1) = \max_{\beta > \underline{\beta}_1^0} \pi(\beta,1) + \epsilon$ for any small enough ϵ. As a result, $\beta_2^*(1) = \arg\max_\beta \pi(\beta,1)$ and the worker's utility is zero under full information.

For no information, since condition Eq. (19) guarantees that $\underline{\beta}_1^0 > \hat{\beta}_2^2$, we have $\max_{\beta > \underline{\beta}_1^0} \pi(\beta,0) > \max_{\beta > \underline{\beta}_1^0} \pi(\beta,1)$, where the inequality follows from Lemma 3 and $\underline{\beta}_1^0 > \hat{\beta}_2^2$. Hence, if ϵ is small enough, we have $\max_{\beta > \underline{\beta}_1^0} \pi(\beta,0) > \max_{\beta \le \underline{\beta}_1^0} \pi(\beta,1) = \max_\beta \pi(\beta,1) = \max_{\beta \le \underline{\beta}_1^0} \pi(\beta,0)$, where the last equality follows from Corollary 2. The above inequality further implies that the optimal commission rate under no information is greater than $\hat{\beta}_2^2$. Following Lemma 3(iii), the worker's utility is greater than zero under no information. Therefore, the platform's aggregate profit and worker's utility are strictly higher under no information than full information.

Supplemental Analysis Under an exogenous commission rate β, the optimal information policy q depends on the value of β. In particular:

Proposition 12. *Given commission rate β, denote the profit maximizing information policy as q^*. Then there are three cases, based on the value of β:*

(i) β is large. That is, $\lambda(\beta,0) = \bar{\lambda}$. In this case, the optimal information policy q^* can be either no, partial, or full information. Moreover, the worker utility $U(\lambda(\beta,q^*),\beta,q^*) > 0$.

(ii) β is intermediate. That is, there exists $\bar{q} \in (0,1)$, such that $U(\lambda(\beta,\bar{q}),\beta,\bar{q}) = 0$. In this case, the optimal information policy $q^* > \bar{q}$ (partial or full information). Moreover, the worker utility $U(\lambda(\beta,q^*),\beta,q^*) > 0$.

(iii) β is small. That is, $\lambda(\beta,1) < \bar{\lambda}$. In this case, the optimal information policy $q^* = 1$ (full information). Moreover, the worker utility $U(\lambda(\beta,q^*),\beta,q^*) = 0$.

Proof of Proposition 12

We prove the above results based on the definitions of the platform profit and the worker utility. Because we only consider a single demand scenario in this part of the proof, we omit the subscript j which is used to denote the different demand scenarios.

By definition, the worker utility is defined as

$$U(\lambda(\beta,q),\beta,q) = \beta v_A - w_0(W_A + \tau) \tag{109}$$

which is formally defined in Eq. (6). Note that v_A and W_A represent the average value of the acceptable requests and the waiting time for workers under the corresponding acceptance strategy, respective, and they are also subject to the information policy q and commission rate β.

Furthermore, the platform profit in a scenario is defined as

$$\pi(\beta,q) = \frac{1}{\tau + W_A}\lambda(\beta,q)(1-\beta)v_A \tag{110}$$

which is formally defined in Eq. (9).

From the worker utility definition, we can derive the following equation:

$$w_0(W_A + \tau) = \beta v_A - U(\lambda(\beta, q), \beta, q) \tag{111}$$

We can then replace the denominator of the fraction term in the platform's profit:

$$\pi(\beta, q) = \frac{1}{(\beta v_A - U(\lambda(\beta, q), \beta, q))/w_0} \lambda(\beta, q)(1 - \beta) v_A \tag{112}$$

$$= \frac{w_0}{\beta - U(\lambda(\beta, q), \beta, q)/v_A} \lambda(\beta, q)(1 - \beta) \tag{113}$$

Our next step is to analyze the profit function $\pi(\beta, q)$ and verifies it satisifies a number of monotonicity properties. A key step of the proof relies on the arrival rate $\lambda(\beta, q)$, which is defined as the minimum of the size of the worker pool $\bar{\lambda}$, and the largest λ such that $U(\lambda, \beta, q) = 0$ which is denoted as $\lambda^*(\beta, q)$. (Formal definition can be found at Eq. (7).)

Thus, by the definition of $\lambda(\beta, q)$, when $\lambda^*(\beta, q) \leq \bar{\lambda}$, it must hold that $\lambda(\beta, q) = \lambda^*(\beta, q)$, and that the worker utility $U(\lambda(\beta, q), \beta, q) = 0$. When $\lambda^*(\beta, q) > \bar{\lambda}$, it must hold that $\lambda(\beta, q) = \bar{\lambda} > \lambda^*(\beta, q)$, and that the worker utility $U(\lambda(\beta, q), \beta, q) > 0$

Therefore, for the platform's profit, there are two possibilities:

1. $\lambda(\beta, q) = \lambda^*(\beta, q) \leq \bar{\lambda}$. In this case, $U(\lambda(\beta, q), \beta, q) = 0$, and it must be true that

$$\pi(\beta, q) = \frac{w_0}{\beta} \lambda(\beta, q)(1 - \beta) \tag{114}$$

2. $\lambda(\beta, q) = \bar{\lambda} < \lambda^*(\beta, q)$. In this case, $U(\lambda(\beta, q), \beta, q) = U(\bar{\lambda}, \beta, q) > 0$, and it must be true that

$$\pi(\beta, q) = \frac{w_0}{\beta - U(\bar{\lambda}, \beta, q)/v_A} \bar{\lambda}(1 - \beta) \tag{115}$$

Furthermore, by Proposition 2, we show that $\lambda^*(\beta, q)$ is weakly increasing in q when β is fixed.

Thus, in the first case, Eq. (114) is increasing in q until the point when $\lambda^*(\beta, q) = \bar{\lambda}$. As a result, if $\lambda^*(\beta, 1) \leq \bar{\lambda}$, then Eq. (114) is increasing in q for all $q \in [0, 1]$, implying that $q = 1$ is an optimal information policy. This proves the third item in Proposition 12.

Now consider $\lambda^*(\beta, 1) > \bar{\lambda}$. If $\lambda^*(\beta, 0) \geq \bar{\lambda}$ also holds, then the platform's problem is equivalent to optimizing for Eq. (115). Note that the only term in Eq. (115) that depends on q is $U(\bar{\lambda}, \beta, q)/v_A$ and $\pi(\beta, q)$ is strictly increasing in this term. Therefore, it must hold that

$$q^* = \arg\max_q \frac{U(\bar{\lambda}, \beta, q)}{v_A} \tag{116}$$

Depending on the shape of $U(\bar{\lambda}, \beta, q)/v_A$, q^* can range from 0 (no information) to 1 (full information). This proves the first item in Proposition 12.

The last case is that $\lambda^*(\beta, 1) > \bar{\lambda}$, and $\lambda^*(\beta, 0) < \bar{\lambda}$. In this case, all information policy q such that $\lambda^*(\beta, q) \leq \bar{\lambda}$ is strictly dominated by $\bar{q}$ which is defined as $\lambda^*(\beta, \bar{q}) = \bar{\lambda}$. Thus, we only need to consider policies with $q \geq \bar{q}$. Moreover, since Eq. (115) is weakly increasing in $U(\bar{\lambda}, \beta, q)/v_A$, it must be true that any strategy with $U(\bar{\lambda}, \beta, q) > 0$ strictly dominates $\bar{q}$. This proves the second item in Proposition 12. □